Essays on the Economics of Community College Students' Academic and Labor Market Success

Mina Dadgar

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ABSTRACT

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Most students who enter a community college with the stated intention of attaining a credential or transferring to a four-year university leave without accomplishing either of those goals (National Center for Education Statistics, 2011). This dissertation attempts to contribute to the growing economic literature that seeks to understand the conditions and policies that can positively influence community college students' academic and labor market success.

In the first essay, I examine the effectiveness of remediation for students who are identified to have the lowest skills in mathematics. Descriptively, while students assigned to remediation tend to have poor outcomes overall, students assigned to the lowest levels of remedial math have the worst outcomes of all students. I use data from the state of Virginia's 2004 cohort of students and use a regression discontinuity design and find that students assigned to the third lowest level of remedial math would have benefited if they had been able to skip that remedial course.

In the second essay, I use administrative data to examine how working while taking classes affects community college students' academic outcomes. I use two different identification strategy: an individual fixed effects strategy that takes advantage of the quarterly nature of the data to control for unobserved and time-invariant differences

among students, and an instrumental variable difference-in-differences (IV-DID) framework that takes advantage of the fact that there is an exogenous supply of retail jobs during the winter holidays. Using the IV-DID framework, I compare academic outcomes during the fall versus the winter quarter for students who are more likely to work in retail versus students who are less likely to work in retail, based on pre-enrollment association with retail jobs. I find small negative effects of working on GPA and possibly positive outcomes of working on credit accumulation.

Finally, in the third essay, Madeline J. Weiss and I examine the returns to community college credentials using administrative data. Using an individual fixed effects identification strategy that compares trajectories of wages across individuals, we find positive and substantial wage returns to associate degrees and long-term certificates and no wage returns to short-term certificates, over and above wage increases for students who enrolled and earned some credits but never earned a credential or transferred. We also find that associate degrees tend to be awarded in low-returns fields, but that in almost any given field, the returns to associate degrees is higher than the returns to certificates.

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Preface

As the United States recovers from the great recession that began in 2009, an educated workforce is essential to maintaining a competitive economy. Once a world leader in educational attainment, the United States ranked 16th in its share of 25–34 year-old degree holders in 2009, falling behind many other industrialized countries (Organization for Economic Development and Cooperation, 2011). While the United States has fallen behind in its supply of college graduates, empirical evidence shows that the demand for educated workers in the United States has only increased. As Autor, Levy, and Murnane (2003) show in their empirical analysis, since the 1970s, technological advancements have caused a decline in the price of "computer capital;" this has resulted in a decrease in employer demand for routine jobs that can be handled by computers, and in an increase in demand for non-routine tasks that complement the work done by computers. This trend, the authors show, has led to differential wage increases for workers who perform routine tasks and those who perform non-routine tasks across industries. This structural change has contributed to the growing wage gap between workers who have college educations and those who have high school educations. At the same time, educational attainment has been particularly low among African Americans and Hispanics, contributing to the historically high income inequality by race in the United States. In 2009, 19% of Hispanics and 29% of African Americans ages 25 to 34 had an associate degree (AA) or higher whereas among Whites and Asians the rates were 49% and 69% respectively (College Board, 2012).

Enrolling 37% of all US undergraduates in 2010, community colleges can help fill this shortage of educated workers (National Center for Education Statistics, 2008). In addition, as open-access institutions that enroll many of the nation's low-income, minority, and first-generation college students, community colleges can help reduce the large gaps in college attainment by different racial group. In July 2009, President Obama called for an additional 5 million community college graduates by 2020 (Inside Higher Ed, 2009). Yet, too many students who enter community college leave without ever attaining a credential or transferring to a four-year university; this is true even for those students who explicitly state their intention to earn a credential upon entry. In 2003–2004, 81% of first time beginning community college students indicated that their intention was to pursue a bachelor's degree (BA) or higher. Yet, six years after initial enrollment, only 11% earned a BA, 14.4% earned an AA, and 8.5% earned a certificate (National Center for Education Statistics 2011). Given this large gap between students' aspirations and outcomes, the question is: What stands in the way of community college students to complete their program and find a "good" job?

Qualitative research that is based on interviews with community college students highlights the long sequence of developmental education that many students have to go through and having to work many hours as being among the key challenges that lead community college students to drop out (Johnson & Rochkind, 2009; Orozco & Cauthen, 2009; Venezia, Bracco & Nodine, 2010). The chapters of this dissertation complement this qualitative research and add to the growing quantitative research that seeks to understand the factors that contribute to community college students' academic and labor market success.

The first chapter examines the effectiveness of community college remediation for students who are identified to be in the lowest skills distribution in mathematics. A majority of students who are enrolled in community college are identified to be unprepared to enroll in college-level courses, and are required to complete one or more non-credit remedial courses before they can take college level courses in the field where their skills have been identified to be deficient. While graduation outcomes are generally poor for students assigned to remediation, they are worst for students who are assigned to the lowest levels of remediation in mathematics. Nationally, only 10% of the students originally assigned to three or more levels below college-level math completed the sequence and passed a college level course in mathematics, referred to as a gatekeeper math course (Bailey, Jeong, & Cho, 2008).

I attempt to understand the effectiveness of remediation for students who are identified as having the lowest skills in mathematics. I use data from the state of Virginia's 2004 cohort of students and take advantage of a regression discontinuity design that compares statistically identical students who are assigned to the lowest level of the mathematics sequence versus the next highest level. The results indicate consistently negative impacts for the lowest level of mathematics remediation on the likelihood of being awarded a degree or certificate.

The second chapter examines how community college students' term-time employment influences academic outcomes including GPA and credit accumulation. Community college students work long hours in paid employment, especially when compared with their counterparts at four-year colleges. For example, according to a report from the National Center for Education Statistics (NCES), in 2007, about 40% of full-time community college students worked 20 hours or more per week compared to 20% of four-year students (Planty et al., 2009). Yet, there is little evidence on the academic consequences of community college students' term-time employment. This is partly because it is difficult to obtain datasets that combine employment and transcript records and partly because it is difficult to find exogenous source of variation for the number of hours students work.

This study takes advantage of a rare administrative dataset from Washington State that combines students' quarterly transcript records with earning records from the state unemployment insurance system. I rely on two causal strategies: first, an individual fixed effects strategy that takes advantage of the quarterly nature of the data to control for unobserved and time-invariant differences among students, and second, an instrumental variable difference-in-differences (IV-DID) framework that takes advantage of the fact that there is an exogenous supply of retail jobs during the winter holidays. I compare academic outcomes during the fall versus the winter quarter for students who are more likely to work in retail versus students who are less likely to work in retail, based on pre-enrollment association with retail jobs. I find small negative effects of working on GPA using both strategies, but the effects of working on credits earned is not conclusive because of the large confidence intervals in the IV-DID model.

The third chapter of this dissertation, which was also my job market paper and is co-authored with Madeline J. Weiss, will examine the labor market returns to different community college credentials using data from Washington State. Community colleges offer a diverse mix of credentials to students, including liberal arts and occupational associate degrees, as well as certificates of different lengths. Associate degrees, which constituted 58% of the share of all credentials in 2010, generally require two years of full-time enrollment to complete while certificates vary in length. The Integrated Postsecondary Data System (IPEDS) categorizes certificates into two groups: long-term certificates, defined as certificates that require one to two years of full-time coursework, and short-term certificates that require less than one year of full-time enrollment to complete (IPEDS, 2010). Possibly as a byproduct of the national policy focus on completion, in the last decade, the number of short-term certificates that community colleges award has increased by 151% nationally, increasing their share of sub-baccalaureate credentials that are short-term certificates from 16% to 25% in only a decade. Because of this national shift toward offering more short-term certificates, it is essential that we understand the labor market value of these credentials. Previous research, with the exception of one recent study by Jepsen, Troske, and Coomes (2012) that uses data from the state of Kentucky, does not distinguish between short- and long-term certificates.

We exploit the Washington State data used in chapter 2 which includes matched, longitudinal college transcripts and Unemployment Insurance (UI) records for the cohort that first enrolled in 2001–2002. Because the UI system in Washington State is one of the few in the country that includes information both on quarterly earnings and quarterly hours worked, we are able to examine the returns to wages (and not just earnings), which provide a more direct interpretation of human capital accumulation. Following Jepsen et al. (2012), we use an individual fixed effects identification strategy and account for the trajectory of wages before, during, and after college attendance. Thus, we improve on previous cross-sectional studies of the returns to community college education that used Mincerian equations and accounted only for observable differences among students by accounting for observable as well as time-invariant unobservable differences among students, such as innate ability or motivation.

We find that earning an associate degree leads to positive increases in wages in almost every field, but that the magnitude of these effects varies greatly by field of credential. For example, while earning an associate degree in humanities and social sciences increases earnings by 5% for women, earning an associate degree in nursing increases women's earnings by 37% (compared with earning some credits but not obtaining a credential). Further, our analysis by field of study reveals that the returns to associate degrees is higher than the returns to long-term and short-term certificates within almost every field, but that a larger proportion of long-term certificates tend to be offered in high-return fields. Our findings also suggest that unlike associate degrees and long-term certificates, short-term certificates have little or no effect on increasing wages in most fields of study compared with earning some credits (average of 30 credits). and not earning a credential Given that the results from the study by Jepsen et al. (2012) also finds minimal or no returns to short-term certificates in the state of Kentucky, we conclude that the dramatic national increase in the number of short-term certificates in the last decade may not have produced a commensurate increase in wages for those earning them. Finally, examining wage returns versus the effects of credentials on increasing the likelihood of employment suggests that much of the returns to earnings estimated in the previous literature resulted from greater employability of students who earned a credential, rather than merely increases in human capital as measured by wages.

The chapters of this dissertation attempt to add to the limited but growing empirical literature on identifying the obstacles and opportunities in the community college students' path to academic and labor market success. Community colleges in the United States rely on less financial resources per student compared with four-year public universities, and yet they serve students who have much less academic preparation and many non-traditional students who work long hours (Bailey & Morest, 2006). The goal of this dissertation is to help community college administrators and policymakers make the best use of the limited resources available to their institutions to help their students succeed.

Chapter 1

Do the Lowest Levels of Remedial Math Generate Positive Effects for Community College Students?

1.1. Introduction

Community colleges, which are open access institutions, provide unique access to higher education for low-income and minority students in the United States (Hoachlander et al., 2003; Levin, 2007). Yet, after enrolling in a community college, many students are identified to be unprepared to enroll in college level coursework, and are required to take one or more non-credit remedial (also called developmental) courses in mathematics, reading, or writing before they are allowed to take any college level courses in those subjects. For example, among the first 27 community colleges participating in the Achieving the Dream initiative, an initiative created to improve developmental education outcomes across community colleges, about 70% of entering students were assigned to take remedial math courses, and half of them were assigned to three levels below college level math (Report of the Developmental Mathematics Redesign Team, August 2010).

With the recent federal and state shift in policy focus from college access to success, low college completion rates for students who have been assigned to remediation have attracted more attention. According to one study, few students who are assigned to remediation complete their remedial sequence and enroll in a college level course in that subject, even after several years. At the same time, students who are assigned to the lowest levels of remedial mathematics tend to have particularly poor outcomes, even compared with students who are assigned to the lowest levels of remedial reading and writing. The study found that nationally, only 10% of the students originally assigned to three or more levels below college level math completed the sequence and passed a college level course in mathematics referred to as a gatekeeper math course (Bailey, Jeong, & Cho, 2008).

These poor outcomes raise questions about the effectiveness of having multiple levels of mathematics remediation to address the needs of low-skills students. For example, it is possible that being required to take multiple courses raises the cost to the student in terms of time and finances, and also increases the opportunities for dropping out, such that this increased cost outweighs any benefits of remedial instruction. Alternatively, it is possible that students with very low skills would have even worse outcomes in the absence of remediation. The answer to these questions has important policy implications. For example, in some states like Indiana, poor outcomes for students who are assigned to the lowest remedial level have been interpreted to suggest that such students do not have “the ability to benefit” from remediation or college coursework; these students are then instead placed into basic skills courses, which have not had better outcomes for students, at least descriptively. Other states have recognized that the length of the remedial sequence and multiple opportunities to exit college contribute to poor outcomes and have introduced reforms to redesign the developmental sequence to reduce the length of the sequence and the opportunities for exiting college. Therefore, causal studies on the effect of the remedial sequence for students who are assigned to different levels of the sequence have direct policy implications for improving the outcomes of students assigned to remediation.

In recent years, several causal studies on the effectiveness of remediation have attempted to examine whether taking an additional course in the remedial sequence improves or worsens outcomes for students who are identified to be at the margins of needing remediation. Using quasi-experimental methods, these studies compared students who were assigned to remedial education with statistically similar students who were not required to enroll in remedial classes. These studies, with the exception of one recent study by Boatman and Long (2009), focused exclusively on evaluating the effectiveness of the highest level of the remedial sequence and did not consider the effect of remediation on students who were identified to have very low skills. The findings of these studies were that remediation failed to benefit—and may have even harmed—students who were required to enroll in one level of the remedial sequence, especially when long-term outcomes such as likelihood of graduation are considered. Bettinger and Long (2009), using data from the state of Ohio, took advantage of variation in institutional placement policies and used distance-to-college as an instrument for assignment to remediation. The authors found positive effects for assignment to mathematics remediation on college persistence. Calcagno and Long (2008) used data from Florida and relied on a regression discontinuity design, comparing students who scored just below and just above the threshold for remediation on the placement score. They found no positive effects from mathematics remediation on long-term outcomes such as earning college credits or graduating, despite positive effects on increasing persistence to the second semester. Similarly, using data from Texas and using a regression discontinuity design, Martorell and McFarlin (2009) found no positive effects from being assigned to mathematics remediation on academic outcomes including persistence, graduation, transfer, or post-college wages for students at the margins of remediation.

A priori, it is likely that the effect of being required to take an additional class in remedial mathematics is different for students with very low skills compared with students just at the margins of remediation. For example, it could be that for students who have very low skills and who are placed into multiple levels of remediation, taking remedial classes is particularly necessary and helpful. In contrast, it could be particularly devastating for students who are assigned to multiple levels of remediation to learn that they are required to take three semesters of non-credit coursework as opposed to having to take just one or two remedial classes, and the expected cost in terms of time and tuition may encourage students to drop out.

Boatman and Long's 2010 study is the only quasi-experimental study that examined the effect of being assigned to remedial classes for students at different levels of ability, including the lowest level of remedial mathematics. The authors found that remedial courses do differ in their impact for different levels of the remedial sequence. They found the most negative effects for students who were assigned to only one remedial class. For students with much lower preparation who were assigned to taking multiple remedial classes, the negative effects of remediation were smaller and were in some cases positive. The results for the effects of the lowest level of remedial mathematics at community colleges were estimated with large standard errors, which makes it difficult to make firm conclusions; however, the point estimates suggest that being assigned to the lowest level of mathematics remediation increases persistence but decreases college credits completed by 1.2 credits and reduces the likelihood of earning a credential by about 5 percentage points.

In addition, a descriptive study by Jenkins et al. (2009) found that participation in most levels of remediation was associated with negative outcomes for students. Jenkins and colleagues used the same data that is used in the current study, which includes the cohort of students that first enrolled in fall 2004 at one of Virginia's 23 community colleges, and concluded that enrolling in the lowest level of developmental mathematics was associated with negative academic outcomes, including taking and passing gatekeeper mathematics and receiving a credential within four years. However, these results only provide suggestive evidence, because students who are assigned to the lowest level of remediation differ from other students, even after controlling for observable covariates.

This chapter attempts to add to the causal evidence on the effectiveness of the lowest level of remedial mathematics that was presented by Boatman and Long (2010) in their study on Tennessee. I examine the effectiveness of the third level of math remediation (which in most colleges is referred to as "Pre-Algebra" and is often the lowest level of remediation offered at a college), compared with the middle level of remediation in mathematics. I use the same data that is used in the descriptive study by Jenkins and colleagues, which includes remediation placement scores, demographic characteristics, course enrollments, placement cut-off scores for different colleges, as well as outcomes, including whether or not a student passed the gatekeeper math course or earned a credential or transferred within four years. In order to account for both the observed and unobserved differences among students who are assigned to different levels of remediation, I follow the previous quasi-experimental studies on remediation and use a regression discontinuity design in which I compare the outcomes of students who scored just below their colleges' cut-off score for the third lowest level of remediation, with the outcomes of students who scored just above the cut-off (assignment threshold). I find that being assigned to three levels of remediation (as opposed to two) reduces the likelihood of earning a community college credential by 9 to 15 percentage points, while the results on whether remediation helps or hurts students' chances of taking and passing gatekeeper mathematics are unclear.

1.2. Mathematics Remediation at the Virginia Community College System

Since 2009, Virginia has been redesigning its traditional model of mathematics remediation into a holistic reform model that attempts to improve graduation outcomes for students who are identified as unprepared to take college level mathematics. Among several changes to the traditional mathematics sequence, the reforms introduce a modularized course design that can be completed within an academic year or less (Report of the Developmental Education Task Force, 2009). This chapter evaluates the traditional model of mathematics remediation as it existed before the initiation of the current reforms.

Between 2004 and 2009, developmental education in Virginia resembled remediation in most states where students are assigned to three (and in some cases four)[1] levels of a remedial sequence based on the students' performance on standardized test. Under the traditional model, when students enrolled in one of Virginia's community college campuses, they were required to take a placement test to help the colleges determine students' need for remediation. If a student was assigned to any of the three levels below college-level mathematics, the student would be prevented from enrolling in a college-level course in mathematics, but would be permitted to take as many as three classes in other subject areas. While Virginia colleges did not have a centralized policy for exempting students from placement testing, some of the colleges allowed test exemptions if the student scored above a specific threshold on the SAT or the ACT tests.

The placement test that was used in 2004 for remedial placement in mathematics in Virginia was the COMPASS test, which is a computer adaptive placement test currently used by several states for the purpose of remedial placement (see Hughes & Scott-Clayton, 2010 for detailed information on remedial assessment in different states). The mathematics section of the test first determines the level at which students should receive

[1] Three of the colleges have broken down the lowest level of remediation into two levels and require students with very low scores to complete four courses in remediation before allowing them to enroll in a college level class. This does not complicate our analysis because we analyze the effects for students who just missed their colleges' threshold for being placed to two levels below college mathematics.

a comprehensive assessment, based on an initial preliminary assessment. Students who are assessed to have the lowest skills are then given questions from the pre-algebra section of the test. If a student is given the pre-algebra test, then the student is either assigned to the lowest level of math remediation or to the middle level of math remediation, based on the student's score on the test and each college's policy and threshold score.

The lowest remediation course in most colleges is called Arithmetic or Pre-Algebra and in most colleges includes topics of arithmetic principles and computations. For example, according to the 2009–2010 course catalogue from Northern Virginia Community College, the course addresses "whole numbers fractions, decimals, percent, measurements, graph interpretation, geometric forms, and applications." Students who score high enough on the pre-algebra test are assigned to the middle level of developmental mathematics, which in most colleges is referred to as Algebra I. Examples of topics discussed in Algebra I based on the Northern Virginia Community College 2009–2010 course catalogue include "real numbers, equations and inequalities, exponents, polynomials, Cartesian coordinate system, rational expressions, and applications."

1.3. Data

The dataset used in this analysis includes 24,664 first-time community college students who first enrolled in one of Virginia's 23 community colleges in summer or fall of 2004.[2] Of students who have a valid placement test score, 5,440 students took the Pre-Algebra section of the COMPASS exam. Because I am interested in assessing the effectiveness of the lowest level of math remediation, I limit the sample to students who took the Pre-Algebra section of the test.[3]

Several characteristics of the Virginia remediation policy for the period of 2004–2009 provide challenges and opportunities for evaluating the lowest level of math remediation. First of all, during this period, there was no centralized policy about placement cut-scores for assignment to different levels of remediation; rather, these decisions were made at the college level. Another variation among colleges during this period was that three colleges used what they called a "decision zone," in which the college replaced the single assignment threshold with a range within which the academic counselors could help students determine the most appropriate remedial class. Finally, there is the common

[2] Of the 24,664 students in our data set, 12,702 have an assessment score. The main reason for a missing COMPASS score would be that a student was exempted from taking the test because of a high ACT/SAT score. In addition, in 2004 some colleges were still allowing students to take paper and pencil tests instead of computer adaptive tests, and those scores were not recorded in the data system. Although the missing data reduces the power of the analysis, it will not bias the coefficients, because we do not expect that data would be missing disproportionately at either side of the cut-off score.

[3] I refrain from evaluating the effectiveness of other levels of mathematics remediation, because unlike assignment to the bottom level versus the middle level, which is determined by students score on the Pre-Algebra test, assignment to the middle versus highest level of remediation and the assignment to college level mathematics could be determined by the score on more than one section of the COMPASS test, and this may violate the necessary RD assumption that student characteristics are smoothly distributed on either side of the threshold.

challenge with evaluating remediation using regression discontinuity design in situations where students are allowed to take the placement test more than once. While Virginia colleges did not generally allow students to retest, it seems that some colleges may have allowed for retesting. As such, I identify colleges that possibly allowed for retesting using the distribution of the data. In the methods section, I will discuss in detail the implications of these policies for using Virginia data and how I address potential challenges.

For each student, the dataset includes information about the type of degree a student is seeking, as well as students' gender, age, and race and whether a student has taken college level courses while attending high school (dual enrollment status).[4] The two academic outcomes that I examine are: whether the student took and passed a gatekeeper math course in four years, and whether the student received a certificate or degree after four years. Table 1-1 shows the mean of different background characteristics and outcomes for the sample of students who have taken the Pre-Algebra section of the test, and also for the sample that excludes colleges with decision zones or that seem to allow re-testing. As we would expect from national trends, these students have generally poor outcomes. Among students in all colleges, only 10% of students who were required to take the Pre-Algebra section of the test passed the gatekeeper math course within four years and only 11% earned a certificate or an associate degree within four years. This is

[4] I control for whether or not a student has participated in dual enrollment because participating in dual enrollment because taking college courses while in high school may help prepare students for the first year of college.

in contrast to the fact that 57% of students indicated an intention to earn an academic credential upon college entry.

Table 1-1: Sample Characteristics and Outcomes

	General Sample		**Schools with no DZ or Retesting**	
Variable	Mean	Std. Err.	Mean	Std. Err.
Student Characteristics				
Age	23.0	0.1	22.9	0.1
Male	34%	0.006	33%	0.009
Black	31%	0.006	33%	0.009
Asian	3%	0.002	3%	0.003
Hispanic	4%	0.003	4%	0.003
Participation in Dual Enrollment	5%	0.003	7%	0.005
Intend to Pursue an Academic Credential	57%	0.007	48%	0.009
Outcomes				
Received a Credential	11%	0.004	11%	0.006
Passed Gatekeeper Math	10%	0.004	8%	0.005
Number of Students	5394		2864	
Number of Colleges	23		15	

Source: Author calculations using data from Virginia Community College System
Notes: the Sample is limited to students who have valid test scores on the Pre-Algebra section for the mathematics placement test.

1.4. Empirical Strategy

In analyzing the effectiveness of the lowest level of mathematics remediation, it is important to fully control for all the observable and unobservable differences between students who took the lowest versus the middle level of remedial mathematics (in Virginia referred to as Pre-Algebra and Intermediate Algebra accordingly). Following

Calcagno and Long (2008), Martorell and McFarlin (2009), and Boatman and Long (2011), I use a regression discontinuity framework. Taking advantage of the fact that each college in Virginia uses a well-documented score threshold for placement into different levels of remediation, I compare outcomes of students who scored just above the assignment threshold with the outcomes of students who scored just below the threshold. While we expect that the two groups of students will be very similar on average, those who score just below their colleges' assignment threshold are required to take an additional remedial class.

If assignment to remediation perfectly predicted enrollment, we would have estimated a reduced form equation such as equation 1.

Equation 1:

$$Y = \alpha + \beta(below) + \kappa(Compass\ distance \times below) + \lambda(Compass\ Distance \times above) + \delta X + \varepsilon$$

Where *below* is an indicator that the student scored below the threshold for the lowest level of remediation and was thus assigned to the third lowest level of mathematics and *above* is an indicator that the student scored above the threshold and is assigned to the middle level of remediation. *Compass distance* is the distance between a student's score on the COMPASS test and the cut-off score of the college that the student is enrolled in. As mentioned earlier, in Virginia during the period of this study, each college chose its own assignment threshold; therefore, in order to obtain a standardized score for each student, I subtract each student's test score from the cut-off score of the students' reported college of attendance. *X* is a vector of covariates including gender, race, age, as well as indicators for prior participation in dual enrollment, and whether the student has indicated intent to pursue an academic or vocational credential upon entry. ε is an idiosyncratic error term. The two separate interactions between COMPASS distance and whether the student has scored above or below the assignment threshold, (*Compass distance* × *below*) and (*Compass distance* × *above*) allow for the effect of distance on the outcome to vary depending on whether the student has scored above or below the cut-off score.

Equation 1 provides "sharp" RD estimates of the effect of scoring below the college's remediation assignment threshold for the lowest level of remediation, not the effect of *enrolling* in the lowest level of remediation. If there was perfect compliance with placement recommendations based on students' compass score and the assignment threshold, the two effects would have been identical. However, not all students that are assigned to the lowest level of remediation enroll in that course (non-compliance), and therefore assignment does not perfectly predict enrollment. Because of the issue of non-compliance, I use the placement score as an instrument to predict enrollment in the lowest level versus the middle level of mathematics remediation using the framework of a fuzzy regression discontinuity design (FRD).

The FRD includes a two-stage equation as shown in 2(a) and 2(b) below. Equation (2a) uses the discontinuity rule as an instrument to predict the effect of scoring below the threshold on enrolling in the lowest level of remedial math. Then, in the second stage, 2(b), I estimate the effect of predicted assignment to the lowest versus the middle level of remediation, on different outcomes. I use the following outcomes as indicators of student success: completing the first gatekeeper course in mathematics (College Algebra) with a grade of C or higher and earning a credential in four years.

Equation 2(a):

$$P = \lambda + \psi(below) + (Compass\ distance \times below)$$
$$+\varphi(Compass\ Sitance \times above) + X\phi + \varepsilon$$

Equation 2(b):

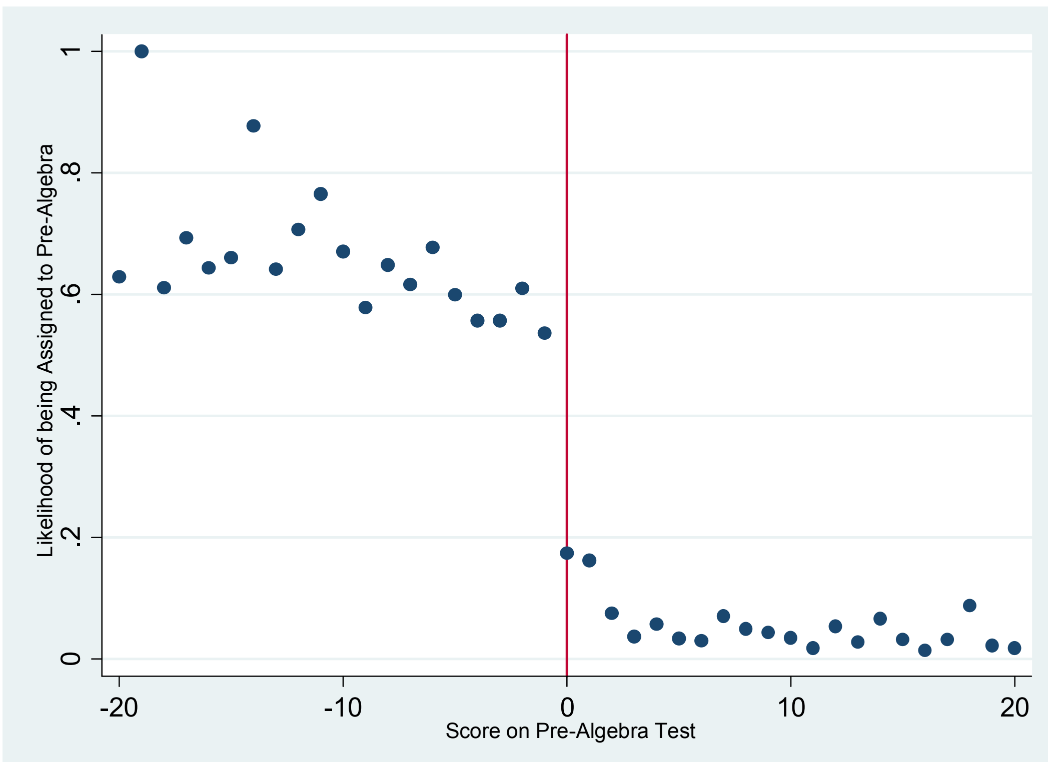
$$Y = \alpha + \beta\left(\hat{P}\right) + \varsigma(Compass\ distance \times below)$$
$$+\pi(Compass\ distance \times above) + X\delta + \varepsilon$$

In the equations above, P represents actual enrollment in the lowest level of remediation (Pre-Algebra), $P\hat{}$ represent predicted enrollment in Pre-Algebra, and all other variables are the same as defined in equation (1). I estimate the two stage model, with both a linear and a squared term, measuring the distance between a student's test score and the cut-score at the students' college.

In order to obtain unbiased estimates using this framework, it is necessary for two main assumptions to hold. First, there should be a discontinuity in the probability of treatment at the cut-off score. In other words, scoring just below the college's threshold score should significantly (and substantively) increase the likelihood that a student will enroll in the lowest remedial class compared with if the student had scored just above the threshold. This first assumption is testable. Figure (2) shows the probability of enrolling in the lowest versus the middle level of remediation by students' score on the Pre-

Algebra section of the COMPASS test. As we would expect, there is a discontinuity in the probability of taking Pre-Algebra at the threshold score (the scores are centered at zero). Estimating the first stage in equation (2a) indicates that scoring below the cut-off score in each college increases a student's likelihood of enrolling in Pre-Algebra (the bottom level of remediation) by 48% and that the difference is significant at $p < .01$.

Figure 1-1: Probability of Enrolling in Pre-Algebra by Compass Score



Source: Data from the Virginia Community College System.
Notes: Score on the Pre-Algebra is centered on 0. Only 20 points below and above zero are represented in the graph

Figure 1-2: Percent Black by Compass Score

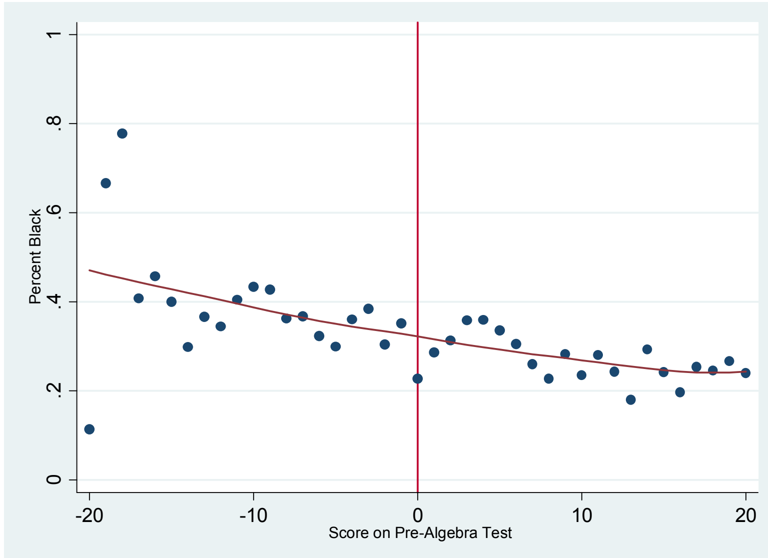


Figure 1-3: Percent Hispanic by Compass Score

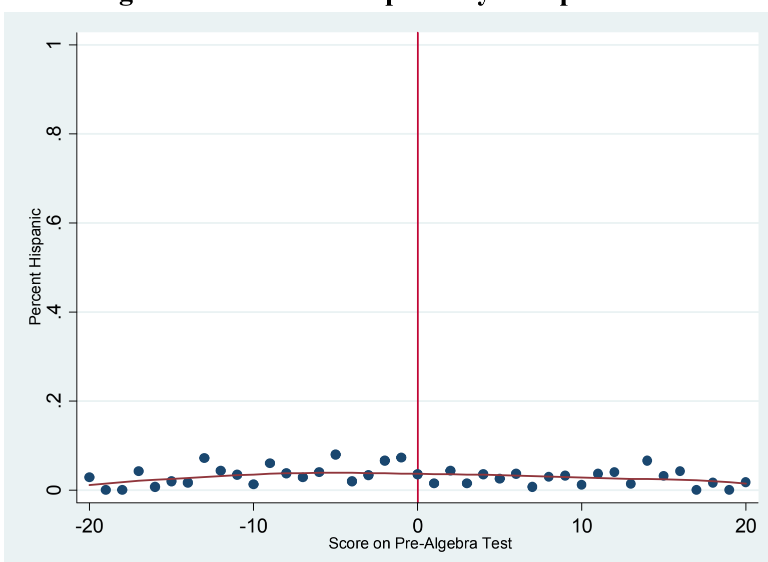


Figure 1-4: Age by Compass Score

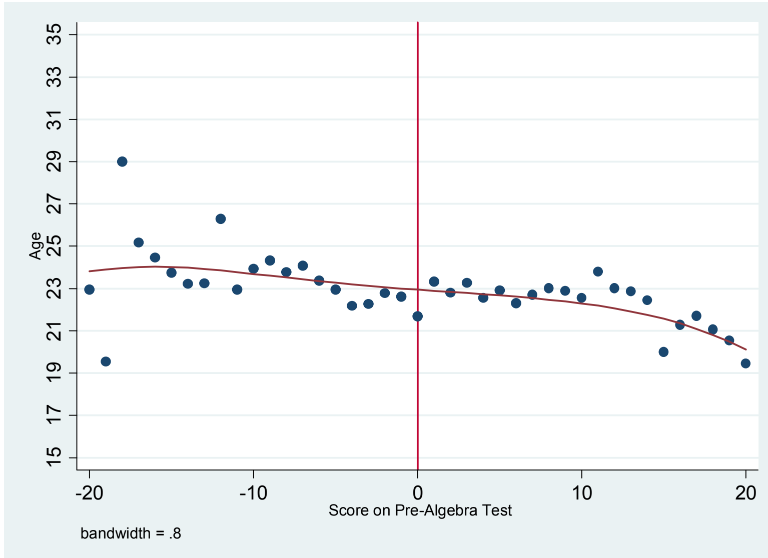
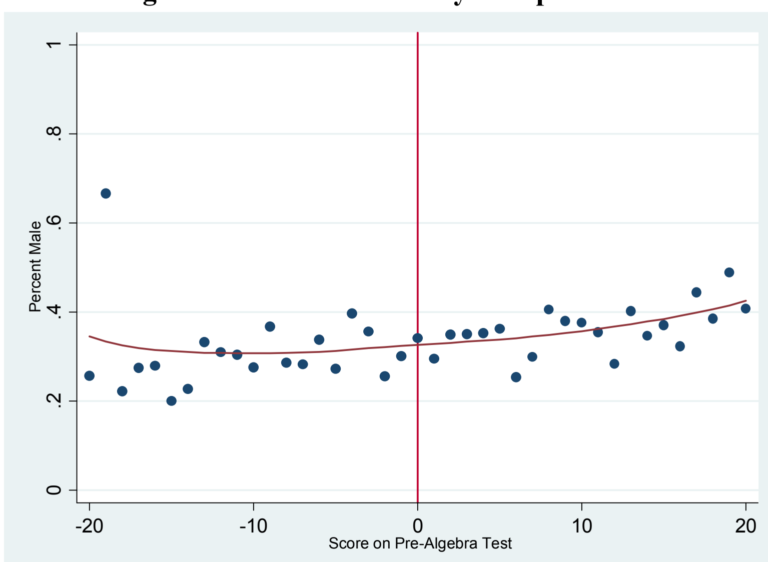


Figure 1-5: Percent Male by Compass Score



Another condition that is necessary to exist for unbiased estimation using RD is that observable and unobservable student characteristics do not change discontinuously on either side of the threshold score. Unfortunately, it is impossible to test this assumption for unobservable student characteristics; however, if observable student characteristics are discontinuous at the assignment cut-off, then we have reason to believe that students are not randomly distributed on either side of the assignment threshold. Figures 1-2, 1-3, 1-4 and 1-5 show the distribution of different observed covariates showing that the distribution is in fact smooth around the cut-off score. In addition, I test whether, on average, student characteristics are similar on either side of the cut-off score. Table 1-2 shows the average student demographic characteristics, the intent to earn an academic credential and prior dual enrollment participation, for the global sample as well as for the more limited samples including students who score within 6 points around their colleges' cutoff score. As we would expect, when we compare all students who scored above the Pre-Algebra assignment threshold (referred to as "all above" in Table 1-2) with all the students who score below the threshold (referred to as "all below" in Table 1-2), there are statistically significant (but small) differences in student characteristics. However, when we compare the differences among the two groups for students within 6 point score range from their college's cut-off score, there are almost no statistically significant observable differences among these students, suggesting that, at least based on observed differences, students who scored 6 points above versus 6 points below the colleges' assignment threshold are similar. This is suggestive evidence that with a narrow bandwidth of 6 points around the cut-off score, we would expect to be comparing similar students.

Table 1-2: Student Characteristics by Assessment Score

Variable	**All below**	**All above**	**Difference**		**(+6)**	**(-6)**	**Difference**	
Age	22.443	23.574	1.131	*	22.650	22.696	-0.046	
Male	0.385	0.305	-0.080	*	0.312	0.340	-0.029	
Black	0.249	0.372	0.123	*	0.023	0.033	-0.011	
Asian	0.026	0.026	0.000		0.031	0.052	-0.021	
Hispanic	0.027	0.044	0.017	*	0.331	0.320	0.011	*
Participation in Dual Enrollment	0.064	0.037	-0.027	*	0.058	0.043	0.014	
Intend to Pursue an Academic Credential	0.597	0.543	-0.054	*	0.595	0.561	0.035	

Source: Author calculations using data from Virginia Community College System
Notes: the Sample is limited to students who have valid test scores on the Pre-Algebra section for the mathematics placement test. “All above” and “all below” refer to samples that include all students that scored above and the sample that include all the students that scored below their colleges’ threshold on the Pre-Algebra test respectively. * Means the difference is significant at the 0.05 level.

In addition to the assumptions mentioned above, there are other potential challenges in using a regression discontinuity design in this context as well as in other similar contexts. The main shortcoming of studies that use regression discontinuity design, which this study partly overcomes, is that the results are only generalizable to students who score around the assignment threshold and not to students with much higher or lower skills. For example, in Florida and Texas where all colleges share a centralized placement cut-score, the number of students that the effect of remediation is estimated for is limited to very few students around the centralized cut-score. One advantage of the Virginia data that helps to at least partly overcome this methodological shortcoming is that during the period of this study, each of the 23 colleges in Virginia were using a different threshold for assigning students to the lowest level versus the middle level of math remediation, and the cut scores covered a wide range. For the bottom versus the middle level of remedial mathematics, the assignment threshold ranges from 29 to 40 points in a 100-point scale. The particularly wide range of cut-off scores in Virginia is ideal in extending the generalizability of the results across a wider range of students.

At the same time, having multiple assignment cut-scores can be a potential challenge for this analysis. If students chose their college based on cut-score in order to avoid remediation, then we would have endogenous sorting around the cut-off score, which would lead to biased estimates. However, this possibility is not likely in general, and particularly not likely in the context of Virginia. Qualitative research reveals that community college students are generally unaware of college remediation policies or even the existence of remedial assessment before enrolling in college (Venezia, Bracco, & Nodine, 2010). In addition, in Virginia, colleges are not located close enough from one another to allow much choice for students with regard to which college to attend.

Several other characteristics of the Virginia system pose potential challenges for this analysis. As mentioned earlier, three colleges in Virginia have a range of scores in which an academic advisor can help students determine which level of remediation to enroll in. The decision zones can lead to endogenous sorting of students around the cut-off score in the colleges that have this policy, because students who score in the range of the decision zone are not randomly assigned to classes, but are instead assigned to classes based on characteristics that may be unobservable to the researcher but are observable to the college academic advisor- and those unobserved characteristics can determine college outcomes. In order to address this complication, I test the robustness of the results to excluding the colleges that have decision zones by re-estimating the results after excluding the three colleges that report having decision zones.

Like other states such as Florida, a main concern using Virginia data is that some colleges may allow for students to re-take the COMPASS exam and only record the highest COMPASS score. Because more motivated students may be more likely to retake the exam, retesting can cause endogenous sorting around the cut-off score. Since there is no central documentation of which colleges allow retesting, I directly test whether colleges show evidence of endogenous sorting by examining the histogram of test scores around the cut-off scores. I identify five colleges that show evidence of possible retesting because there is a stacking of test scores just above the cut-off score. In order to test whether or not this potential bias is driving the results, I re-run the analysis after excluding those five colleges that show evidence of possible stacking of test scores above their cut-off score.

1.5. Results

In this section, I estimate the effect of enrolling in three levels below college level mathematics versus the effect of enrolling in the middle level of college mathematics on two different college outcomes, including the likelihood of passing a gatekeeper course in mathematics and of receiving an associate degree or a certificate (hereon referred to as a credential) within four years after initial college enrollment.

Since there is no consensus over the correct method to find an optimal bandwidth, I display the results with different bandwidths (as well as different specifications) and discuss the sensitivity of the results to different bandwidths. In general, when in choosing a bandwidth, we expect the least bias when students with very similar scores are compared. At the same time, the tradeoff is that as the bandwidth becomes narrower the small sample size becomes smaller and the estimates become less reliable. While different propositions for estimating an "optimal" bandwidth are suggested, each method depends on a set of untestable assumptions (Imbens & Lemieux, 2008). Therefore, I show the results using different bandwidths and test their robustness to different samples and specifications.

Table 1-3 shows models with different specifications that estimate the effect of enrolling in the third lowest level of mathematics remediation versus the next highest level using equation (2b). Model 1 represents the global results that include all students who took the Pre-Algebra test regardless of COMPASS score, but which controls for observable differences among students and the distance between the students' scores and their colleges' placement cut-scores. Models 2, 3, 4, and 5 limit the comparison to students who scored within different bandwidths around the cut-off score for their college including +/-10 points, +/- 8 points, +/-6 points, respectively. Model 5 reports the global results but adds separate squared terms for COMPASS scores above and below the cut-off to allow for a non-linear relationship between the COMPASS score and college outcomes; it also adds college-fixed-effects that control for all the observable and unobservable differences among colleges by comparing students within the same college.

Table 1-3: Instrumental Variable Estimates of Enrolling in the Third Lowest Level of Math Remediation

Dependent Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Received a Credential in 4 Years	-0.0884*	-0.081	-0.139	-0.146	-0.0884*
	(0.050)	(0.094)	(0.116)	(0.126)	(0.050)
Bandwidth	Global	(+/-10)	(+/-8)	(+/-6)	Global
Includes Distance from cut-off squared					X
Includes College Fixed Effects					X
Observations	5,110	2,930	2,470	1,918	5,110
Passed Gatekeeper Math	-0.0472*	-0.023	-0.011	0.010	-0.044
	(0.028)	(0.047)	(0.056)	(0.074)	(0.049)
Bandwidth	Global	(+/-10)	(+/-8)	(+/-6)	Global
Includes Distance from cut-off squared					X
Includes College Fixed Effects					X
Observations	5,440	3,118	2,627	2,047	5,110

Source: Author calculations using data from Virginia Community College System
Note: Standard errors are shown in parentheses. Covariates include gender, age, and intent including academic/transfer or workforce credential, as well as dual enrollment status. All models include covariates and distance from cut-off score.

As Table 1-3 shows, enrolling in Pre-Algebra reduces the likelihood that a student will earn a credential within four years. According to these results, enrolling in the lowest versus the middle level of remedial mathematics reduces the likelihood of earning a credential in four year by 9 to 15 percentage points. These results are highly robust to different bandwidths and specifications. By contrast, when the outcome of interest is the likelihood that the student passed gatekeeper mathematics, the results are not robust and the coefficients change sign with choice of bandwidth; thus, even though most of the coefficients are negative, we cannot make firm conclusions from those results about the potential effects of the lowest level of remediation on the likelihood of passing gatekeeper mathematics.

A final sensitivity check tests whether the results are robust to excluding colleges that allow re-testing or have decision zones, a range of scores where the counselors can help students decide which course the students should enroll in. In the case of both decision zones and retesting, the assumption that students just below and just above the cut-off are sorted randomly and thus are comparable is violated. To address the issue raised by the existence of decision zones, I re-estimate the models, excluding the three colleges that have indicated that they have decision zones for the Pre-Algebra section of the COMPASS test. I show that the negative results for credential attainment within four years is not sensitive to the exclusion of colleges that have retesting or decision zone. While there is clear documentation identifying the colleges that have decision zones, there is no documentation regarding which colleges allow retesting. In fact, most colleges state that they do not allow students to re-test under normal circumstance; in addition, there is no centralized information on the degree to which retesting may occur at some colleges. Therefore, I use the data to identify colleges that may have retesting, in order to test whether the inclusion of those colleges is driving the negative results. To do so, I plot the histogram of Pre-Algebra test scores for each college to identify the colleges in which there is stacking of test scores just above the college cut-off score, which would indicate that the college may be allowing the students to retest. I identify five colleges that have unsmooth distribution of test scores around the college’s assignment threshold.

Table 1-4 shows the analysis results after the three colleges with decision zone are excluded and then after colleges that show evidence of re-testing are excluded. We can see that the results for obtaining a credential in four years are highly robust to excluding either colleges with decision zones or colleges with retesting. These results closely approximate the main result, although they increase the range of the negative effects, suggesting it could lie between -3% to -20%. The results for passing Pre-Algebra, by contrast, are highly sensitive to which colleges are excluded from the sample. Thus based on both the main model and the sensitivity checks, we can conclude that the Virginia data suggests that enrolling in the lowest level of remediation as opposed to the middle level reduces students' likelihood of receiving a credential, but that is unclear how enrollment in the lowest level of remediation affects the likelihood of passing the gatekeeper course in mathematics.

Table 1-4: Sensitivity Checks

Sensitivity Checks- Excludes Students at Colleges that have Decision Zones				
Dependent Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Received a Credential in 4 Years	-0.107*	-0.027	-0.100	-0.109
	-0.059	-0.089	-0.099	-0.098
Includes Covariates & Distance from cut-off	X	X	X	X
Bandwidth	Global	(+/-10)	(+/-8)	(+/-6)
Observations	3,361	1,978	1,683	1,306
Passed Gatekeeper Math	0.003	0.065	0.079	0.040
	-0.048	-0.073	-0.082	-0.081
Includes Covariates & linear and squared distance from cut-off	X	X	X	X
Bandwidth	Global	(+/-10)	(+/-8)	(+/-6)
Observations	5,440	3,118	2,627	2,047
Sensitivity Checks- Excludes Students at Colleges that may have retesting				
Dependent Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Received a Credential in 4 Years	-0.0980*	-0.106	-0.155	-0.197
	-0.050	-0.095	-0.118	-0.130
Includes Covariates & Distance from cut-off	X	X	X	X
Bandwidth	Global	(+/-10)	(+/-8)	(+/-6)
Observations	4,971	2,847	2,402	1,873
Passed Gatekeeper Math	-0.058	-0.026	-0.035	-0.127
	-0.049	-0.091	-0.113	-0.127
Includes Covariates & linear and squared distance from cut-off	X	X	X	X
Bandwidth	Global	(+/-10)	(+/-8)	(+/-6)
Observations	4,971	2,847	2,402	1,873

Source: Author calculations using data from Virginia Community College System
Note: Standard errors are shown in parentheses. Covariates include gender, age; intent including academic/transfer or workforce credential, as well as dual enrollment status.

1.6. Discussion

This chapter asks the following causal question: Would students with the lowest skills in mathematics have better or worse outcomes if they were required to take only two remedial classes, rather than three? The answer from Virginia's data is that, at least for students who are at the margins of being assigned to the lowest level of remediation, being required to take two rather than three remedial classes would have increased the likelihood of attaining an associate degree or a certificate in four years by 9 to 15 percentage points. These negative effects are very large, given that on average only 11 percent of students who take the Pre-Algebra test earn a credential in four years.[5] Boatman and Long (2010) provide the only other causal estimate in the literature that includes students who are required to take multiple remedial classes in mathematics; my estimates are similarly negative for a timely awarding of credentials but are somewhat larger in magnitude. For their estimates of the effect of the lowest level of remediation in mathematics, Boatman and Long found that remediation reduces the likelihood of credential completion by 5 percentage points. There are no other estimates for the effect of taking the lowest level of remediation on passing gatekeeper mathematics, thus I am not able to put those estimates in the context of previous studies.

One of the limitations of the different causal studies of effectiveness of the traditional model of remediation is that because most of the studies use a regression discontinuity framework, the results are only generalizable to those students whose score on the placement test is near the placement threshold score. This particular methodological challenge is less of a problem in Virginia, compared with states where all

[5] Some of this effect may not be the effect of assignment to remediation rather than enrollment. Students may drop out of college after learning they have to enroll in three levels of remediation.

colleges follow a single centralized cut-score, because colleges in Virginia have great variation in placement cut-scores, and therefore, the results from this chapter can be generalized over a range of different placement scores.

A shortcoming of this study and other previous causal studies is that it is impossible to know exactly why the traditional model of remediation is ineffective. It is likely that the negative effects of having to expend additional time and money outweighs any positive effects of instruction. Therefore, these large negative effects could be present even when the quality of instruction is very good. We can develop different hypothesis for other mechanisms that contribute to the negative effects of the lowest level of mathematics. These include both the direct costs and the opportunity costs of taking three remedial classes. According to Jenkins et al. (2009), one plausible explanation for poor outcomes is that students who are assigned to the lowest level of remediation meet multiple points at which they could "leak" out of their path to completion. Another reason may be that being required to take multiple courses for no credit increases the time to degree so much that the students will simply leave college before completing the remedial sequence and enrolling in a college level course, and will never have a chance to "catch-up" to other students (Boylan and Saxon 1999; Bailey, 2009). Qualitative analysis will be able to reveal more information about the mechanisms that can contribute to the success or failure of remediation.

Another important causal question that this study is unable to address is whether students with very low skills would benefit or be harmed if all levels of remediation were removed and every student was directly placed into college-level mathematics courses.

While the quasi-experimental literature on remediation, when viewed as a whole, suggests that mathematics remediation is ineffective at every margin of remediation, it does not necessary follow that a student at the bottom level of remedial math could be placed into college level mathematics and not be harmed. This is because the regression discontinuity design only allows for estimating the impact of skipping one level of remediation and not multiple levels. At the same time, descriptive evidence presented by Jenkins and colleagues shows that greater numbers of students fail to re-enroll in multiple levels of the remedial sequence, compared with the number of students who fail each course in the sequence (Jenkins et al., 2009). If it is the multiple exit points, rather than poor academic preparation that is the driving force for the poor outcomes of students assigned to developmental education, as the descriptive evidence suggests, any attempt to reduce or eliminate the exit points, including mainstreaming students with any skill level into college level courses, is likely to improve outcomes. Future quasi-experimental research is necessary to determine whether alternatives to the traditional models of remediation that reduce the number and length of remedial courses improve the rates of credential attainment and timely completion of gatekeeper math courses for students with very low initial skills.

As mentioned earlier, since 2009, the state of Virginia has introduced a plan redesign of its developmental education sequence. According to this plan, starting in the spring of 2012, developmental mathematics will be taught as a series of nine one-credit modules, and students will only take the modules in which the diagnostic placement test has indicated a need for improvement and is required for the students' field of study

(Asera, 2011). The goal is specifically to reduce the number of exit points and the time required to complete remediation. The reforms also aim to improve the actual course content and delivery through means such as better alignment of remedial coursework with college level math courses, and also by providing more professional development for course instructors (Developmental Education Task Force, 2009). Given the finding of this chapter that students assigned to the lowest level of remediation would have been helped if they could have skipped that level of remediation, we would expect that the redesign would improve the outcomes for the students who have been identified as most underprepared. Evaluating the new modularized and accelerated model of remediation in Virginia and elsewhere and comparing its effectiveness to that of the traditional sequence can help inform similar attempts at reform in other states.

Chapter 2

To Work or Not to Work: The Academic Effects of Working While Enrolled for Community College Students

2.1. Introduction

Community college students often work long hours in paid employment, especially when compared with their counterparts at four4-year colleges. For example, according to a report from the National Center for Education Statistics (NCES), in 2007, about 40% of full-time community college students worked 20 hours or more per week compared to 20% of four-year students (Planty et al., 2009). Furthermore, interviews with students who had dropped out from college revealed that the students believed that inability to balance work and school had played an important role in their decision to leave college. A recent, nationally representative survey of 614 adults reported that students who had left college identified having to work long hours as the main challenge to staying in college (Johnson & Rochkind, 2009). In a report titled *Work Less, Study More, and Succeed*, published by the non-partisan research and advocacy group DEMOS, the authors conclude that based on qualitative and descriptive research, the main cause of high drop-out rates among community college students is term-time employment, working in paid employment during the course of a semester or quarter. They claim that providing more financial aid to low-income students is the key to improving college graduation rates (Orozco & Cauthen, 2009). However, despite the prevalence and intensity of employment among community college students, the low graduation rates of these students, and its potentially important policy implications, there is limited rigorous empirical research on the academic consequences of student employment.

2.1.1. Theoretical Background

Education theory and economic theory provide useful frameworks for studying the consequences of student employment. Tinto's social integration model hypothesizes that a few hours of on-campus work can help integrate students into campus life and increase retention, while long hours of work, especially off-campus work, can have the opposite effect, not only because it limits the available time for students to study but also because it limits opportunities for interaction with other students and faculty (Tinto, 1993). The Human Capital Theory as put forward by Becker (1962) suggests that it may optimal to work only once an individual has completed her education. The reasoning behind this is that education is considered an investment that increases one's human capital, and therefore in the absence of credit constraints, not working until post-graduation can allow the individual to fully reap the benefits of her investment.

However, even in the absence of credit constraints, Yoram Ben-Porath (1967) proposes that it may be optimal to combine schooling with employment if the human capital production function is concave. In other words, due to diminishing marginal returns, as time spent on a given task, such as studying, increases, the benefits of additional time spent on that task decreases. In the presence of such diminishing marginal returns, we could expect that the optimal level of accumulation of human capital includes a combination of school and work. This is consistent with empirical findings for high school students that suggest positive impacts of working on future earnings despite having a negative effect on grades (Ruhm, 1997; Light, 1999). The same pattern may be true for college student employment. In this case, increasing one's work hours could reduce human capital gained through studying, but could also increase one's human capital attained through working. If there were a range of work intensity where the amount of human capital gained through working exceeds the loss of human capital from a reduction in study time, then increasing the hours worked within this range would increase one's total human capital and thus one's post–high school or post-college earnings. However, increasing hours worked *beyond* this range would be likely to reduce total human capital and post-exit earnings. An extreme case would be where a student reduces hours spent on studying so much that she is forced to drop out of high school or college. In this case, the reduction in one's human capital from studying reduces the *total* human capital accumulated and thus reduces post-exit earnings.

Scott-Clayton (2012) lays out various mechanisms for accumulating human capital through employment during college enrollment. She suggests that, for example, work experience in even relatively low-skill jobs could help students "develop soft skills, build career networks, secure references, and/or acquire information that enables better job matches later in life." Another benefit of working could be the acquisition of informal human capital in terms of "portfolio diversification" in the presence of uncertainty about necessary skills in the job market. Finally, working may alleviate credit constraints and thus allow students to continue to enroll or register for more classes, which they would not have been able to afford in the absence of an income from working. In the presence of credit constraints, it may be the case that although working limits students' available time to study, it allows students to pay for the tuition costs of enrolling in more classes. For community college students, given the very high average drop-out rates, it may be reasonable for a student to remain at an existing job and minimize the risk of having to find a new job, as well as the costs associated with job search, in the event that the student leaves college before earning a credential. In fact, in our sample of community college students in the state of Washington, 77% of the students who worked during the first quarter of enrollment worked for the same employer that they worked for prior to college enrollment.

Hypothetically, it is possible that working while in college not only helps students with employment after college exit, but that it even helps students perform better academically. Some types of jobs such as low-intensity, on-campus jobs may help integrate students into campus life as Tinto (1993) would suggest, and certain types of employment may give students motivation, discipline, and structure, and help them to study more effectively. It is also possible that some jobs provide the opportunity for students to interact with educated adults who can serve as mentors or role models and who can inspire students and help them to navigate college. Thus theoretically, the intensity and type of employment can determine whether term-time employment has positive or negative effects on academic and labor market outcomes. *Understanding the Working College Student* (Perna, 2010) includes multiple essays that are based on this theory regarding the intensity and type of employment and features interviews with students about their roles as college students and employees. Perna concludes that work has both benefits and costs to students' educational experiences and outcomes. The book argues that on the one hand, working can benefit students by increasing engagement in effective educational practices and may be associated with higher post-college earnings. On the other hand, the book cautions that, particularly for community college students, working may limit students' integration into academic life or their time to complete class assignments and could therefore harm students' academic achievement.

2.1.2. The Consequences of Student Employment: A Review of the Empirical Literature

The empirical literature on the academic consequences of student employment is mostly descriptive. This literature generally finds a positive association between working a few hours on campus but a negative association for working many hours off-campus (Gleason, 1993; Pascarella et al., 1998; Orszag, Orszag, & Whitmore, 2001; Dundes & Marx, 2007; Orozco & Cauthen, 2009, McCormick et al., 2010). A recent review of the descriptive literature by Riggert, Boyle, Petrosko, Ashe, and Parkins (2006) concludes that there is still much diversity and contradiction in the findings of the studies on student employment, which may be partly attributed to the differences in methodology and outcomes reported. In some descriptive studies, such as Pascarella et al. (1998), the authors control for some preexisting student characteristics including students' pre-college test scores; however, even in carefully controlled studies it is likely that unobserved preexisting differences among students are driving the differences in outcomes.

A handful of quasi-experimental studies have attempted to account for the pre-existing differences among students by using exogenous variation for college students' work intensity. With the exception of one particularly rigorous study by Stinebrickner and Stinebrickner (2003), the quasi-experimental studies have generally found small negative effects on academic performance for college students' employment (Desimone, 2008; Kalenkoski & Pabilonia, 2010; Scott-Clayton, 2011).[6]

The most rigorous evidence to date on the academic consequences of college students' employment is from a study by Stinebrickner and Stinebrickner (2003), which found large negative effects of employment on first semester GPA. The authors used data from 1,200 students at Berea College in Kentucky; all students at Berea College are required to work at least 10 hours per week and are randomly assigned to jobs during their first semester. In addition, some jobs offer work beyond the required hours while

[6] Kalenkoski and Pabilonia (2010) tested for a possible non-linear effect of work intensity by including a quadratic term in the equation, but did not find the coefficient to be significant.

others do not, which allowed the authors to use the initial job assignment as an instrument for hours worked. They found a large and negative effect for an increase in hours worked on first semester GPA, which is several times larger than the effects found by the other quasi-experimental studies on college students' employment. According to the authors, a one hour exogenous increase in hours worked per week reduces GPA by 0.16 points. The main potential limitation of the study by Stinebrickner and Stinebrickner is that the sample is based on students attending Berea College, which is very different from most US institutions in that it is a small college with a particular mission; in consequence, the results may not be generalizable to students attending other four-year colleges or community colleges.

Two studies by Kalenkoski and Pabilonia (2010) and Desimone (2008) used national data and instrumental variables and found small negative effects of employment on college students' academic performance. Kalenkoski and Pabilonia (2010) used the nationally representative NLS-97 sample and constructed an instrument for predicting employment intensity that combines the net price of schooling, parental transfers, county unemployment, the availability of a state work–study program, and the state minimum wage. Desimone (2008) used a sample based on the College Alcohol Study that includes several four-year institutions but no two-year institutions. He used fathers' education conditional on mothers' education, and religion as instruments to predict hours worked. Kalenkoski and Pabilonia found that a one-hour-per-week increase in employment reduced GPA by 0.022 points for students attending two-year colleges and 0.017 points for students attending four-year colleges; Desimone found that an extra hour of work reduced GPA by 0.011 points for four-year college students.

The studies by Desimone (2008) and Kalenkoski and Pabilonia (2010) relied on samples that are much more representative than the sample studied by Stinebrickner and Stinebrickner (2003), but they may have limited internal validity. For example, parental transfers and college costs may be invalid instruments, because parents who invest more in their children's education are likely to have children with greater college achievement regardless of the students' employment decision. Similarly, net college cost may be related to college quality, which may affect students' GPA. Parent's religion and father's education may also be related to children's motivation or study habits, which can affect college achievement.

Scott-Clayton (2011) examines the effect of a specific type of college employment, the federal work–study program, on students' academic outcomes, including first-year GPA and credit attainment, as well as drop-out and degree attainment. She used administrative data from two and four-year colleges in West Virginia and difference-in-differences identification strategy to compare students who are eligible and ineligible for federal work–study at schools that receive high per-pupil allocation of work–study funding with schools that are allocated lower amounts. For first-year academic outcomes including first-year GPA and credits earned, she found that the effects ranged from small and negative to potentially positive, while for longer-term outcomes including drop-out and four-year degree completion, the effects seem to be negative and large in magnitude. She found that a one-hour increase in federal work–study employment decreased GPA by

0.05 to 0.02 points. However, she found positive point estimates for the effect of federal work–study employment on credits earned, suggesting that it is likely that federal work study increases first-year credit accumulation, despite the other possibly negative effects. Scott-Clayton also found large heterogeneity in the results by gender and whether or not the student was a recent high school graduate.

A priori, we would expect that if there are differences in the academic effects of on-campus versus off-campus jobs, then on-campus jobs such as those supported by federal work–study would have more positive (or less negative) effects compared with other types of student employment. For example, as Tinto (1993) suggested, an on-campus job may have positive effects in terms of enhancing social integration. It is also possible that on-campus jobs would be more supportive of students' academic activities and have more flexible hours or more "down time" when students can study. If these assumptions are true, we would expect the effects for off-campus employment to be more negative, compared with the estimates provided by Scott-Clayton (2011) on the effects of federal work–study jobs.

In addition to the literature on college students' employment, there is a rigorous study on the academic consequences of high school students' employment that may have implications for college students' employment. Tyler (2003) used exogenous variation in child labor laws across states to instrument for high school students' work intensity and found large negative effects of high school students' employment on test scores. Using the National Education Longitudinal Study of 1988 (NELS:88) sample, he estimated that a 10 hour per week decrease in high school students' work intensity would lead to a 0.20

standard deviation increase in math scores. While his study is compelling evidence for the negative effects of employment for high school students, it is likely that the effects of employment would be different for college students who may be better at managing their time across various activities and who may have the opportunity to benefit from any positive peer and mentorship effects of employment.

Overall, the evidence on the academic consequences of college students' employment is limited and inconclusive. Desimone (2008), Kalenkoski and Pabilonia (2005), and Scott-Clayton (2011) found small and negative effects of employment on GPA, while Stinebrickner and Stinebrickner found negative effects that are much larger in magnitude. It is not clear whether the differences in results found by Stinebrickner and Stinebrickner and the results found by others is because the other studies contain bias or whether it is because the results found in the sample of Berea College is not generalizable to students attending other institutions. Furthermore, while most studies only considered GPA as an outcome, Scott-Clayton found that the employment offered by the work–study program may have large negative effects when considering the likelihood of drop-out. At the same time, Scott-Clayton found possible positive effects of work–study employment on first-year credit accumulation, which could be because of the positive effects of employment in reducing credit constraints and helping students pay for course tuition.

This study attempts to contribute to the emerging research on the academic consequences of college students' employment by providing one of the first quasi-experimental estimates of the academic consequences of community college students' term-time employment. I take advantage of a rich administrative dataset from

Washington State that combines transcript data with quarterly employment information from the state's Unemployment Insurance (UI) records. Washington State is one of the few states in the United States where UI data contains quarterly hours worked (and not just earnings). The outcomes I am able to use in this dataset include quarterly GPA and credits earned. I use two different identification strategies: the first strategy uses within-student variation in hours worked to predict the effect of a change in hours worked on GPA and credits earned across quarters, using an individual fixed effects identification framework. The second strategy takes advantage of the fact that students who work in retail jobs work much longer hours during the fall quarter, which includes the holiday shopping season. I compare fall GPA with winter GPA, and credits earned for students who are likely to work in retail with students who are not likely to work in retail, based on students' pre-college association with retail jobs.

My findings on GPA suggest small negative effects and are strikingly similar to the findings of Kalenkoski and Pabilonia (2010), the only other study in the literature that examined the consequences of employment for community college students separately.

2.2. Data

This study uses student unit record data from the Washington State Board of Community and Technical Colleges (WSBCTC) matched with employment data from Unemployment Insurance records.[7] The student unit record data include transcripts with quarterly

[7] Unemployment Insurance records include records from Washington State and the nearby states of Alaska, Idaho, Montana, and Oregon, as well as federal, military, and postal service records. Wages and hours

information on each student's courses (including grades), any credentials awarded, and student demographic characteristics (including a proxy for SES created by matching student addresses to Census tract data). The Unemployment Insurance (UI) data includes quarterly information on hourly wage rates, earnings, and industry of employment.

The sample includes all first-time college students who enrolled at a Washington community or technical college in the 2001–2002 academic year, had a valid social security number (and thus could possibly be matched with employment records), were not international students, and were not enrolled through employer contracts (were at least partially "state funded"). I further limit the sample to students whose declared intent includes transferring to a four-year institution, obtaining an academic credential, or participating in a workforce-related program. This limits the sample to 41,353 students, which is the baseline sample used for the descriptive analysis. For the analysis using individual fixed effects, the sample is further limited to students who began in the fall quarter and who attempted some credits during each of the first three quarters of enrollment (*n* = 10,313); for the difference-in-differences analysis, the sample is limited to students who began in the fall quarter and who have attempted credits for at least two quarters (*n* = 12,588). As will be discussed in the methods section, these limitations are necessary to ensure that each analysis obtains unbiased estimates.

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worked from some types of employment (such as self-employment and undocumented employment) may not be represented in this data.

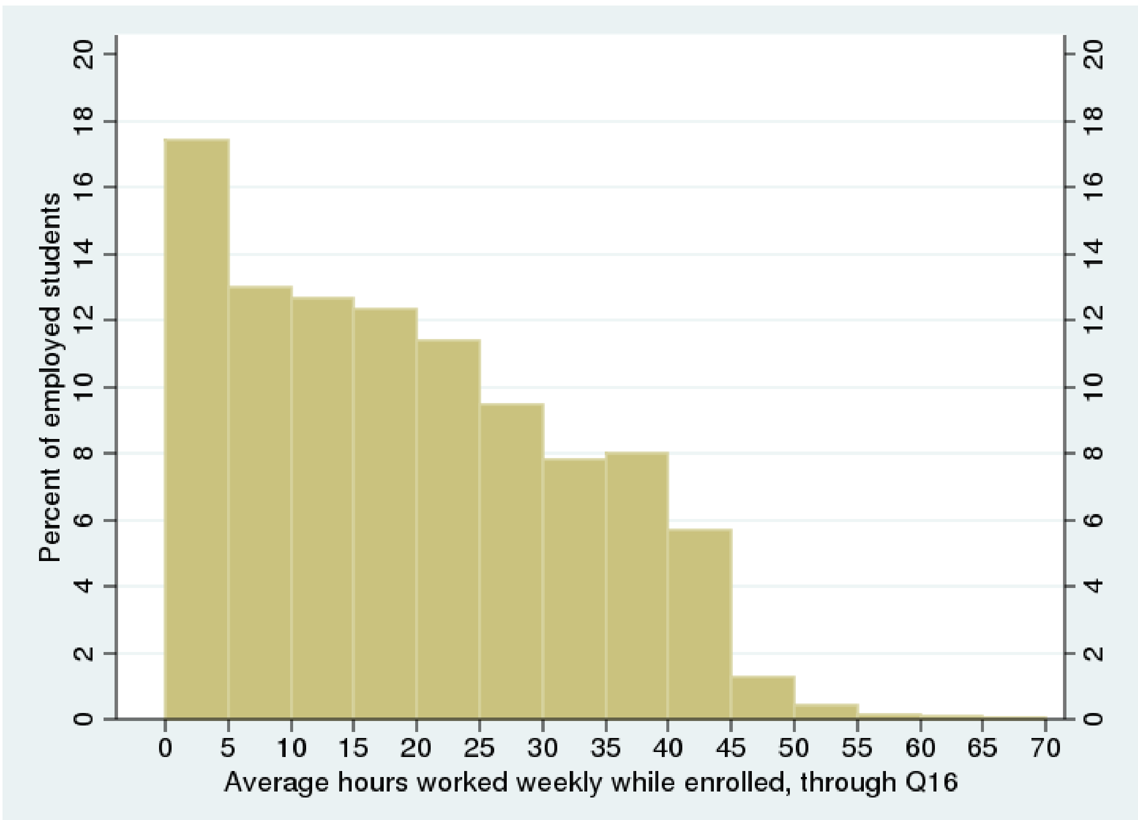
Community colleges enroll many non-traditional students who may be older or who may have workforce intent, and the effect of work intensity may be very different for this group of non-traditional students than for traditional students, who are generally the population of interest for policymakers. Therefore, I also estimate the results for a subgroup of "traditional" students. My definition of "traditional" includes students who are 20 years old or younger at the time of initial enrollment in college, and who declare an intention to pursue an academic (non-vocational) credential or to transfer to a four-year college. I test whether the overall results hold for this sub-sample.

2.3. Describing the Work Situation of Community College Students

In this section, I take advantage of the detailed nature of our administrative data to describe community college students' employment situations while enrolled in college. Because previous studies are often based on national survey data, there is limited information about the students' work situations. I take advantage of the detailed nature of the administrative data from Washington State to describe the distribution of hours worked, the type of jobs community college students work at during college and after exiting college, and how work intensity while enrolled differs by students' demographic characteristics.

Figure 2-1 shows the distribution of hours worked weekly during the quarters of enrollment. Approximately 73% of the students in the full sample worked some hours while enrolled in college, according to Washington State data.[8] Most students worked part time while enrolled. About 45% of the working students in the sample worked for at least 20 hours per week, and 16% worked full time, defined as working at least 35 hours per week.

Figure 2-1: Average Hours Worked Weekly While Enrolled, Employed Students Only



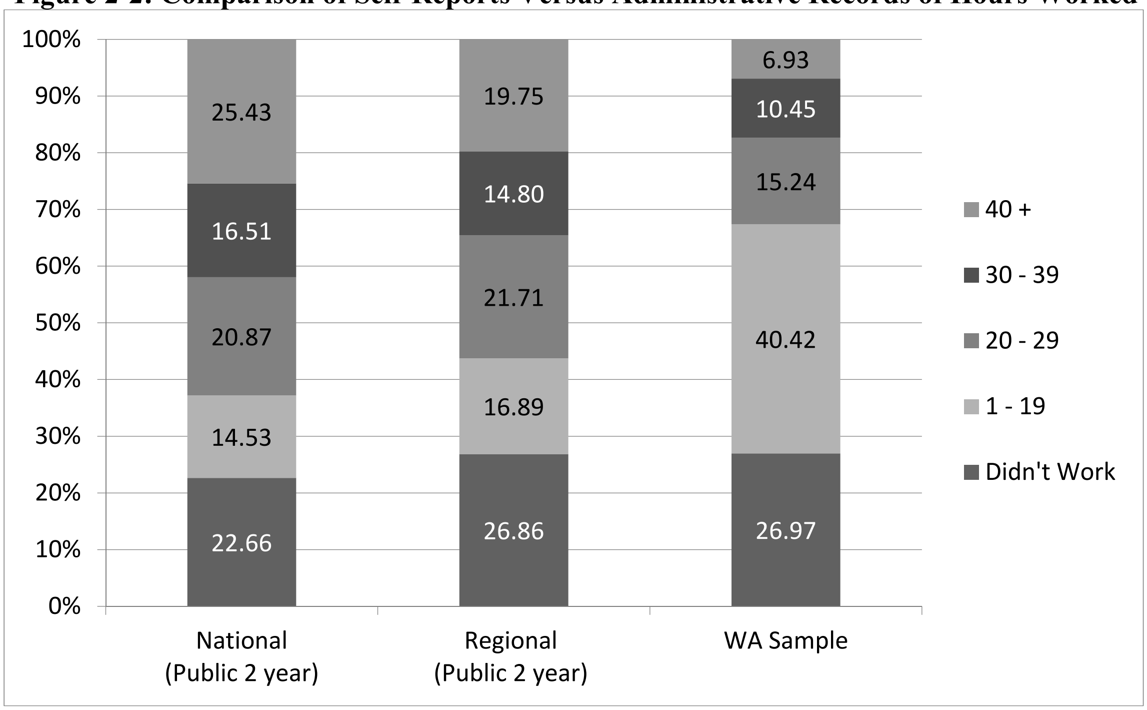
Source: Author's calculations using WSBCTC data and matched employment data from Unemployment Insurance records.
Notes: The sample includes all first-time freshmen who enrolled at a Washington State community or technical college in the fall of 2001, who were at least partially state-funded, had a valid social security number, were not international students, and indicated workforce intent or intent to transfer to a four-year institution.

[8] This number is an underestimation of actual employment to the extent that it may omit work that is self-employed, "under the table," or with employment offices outside Washington and its neighboring states.

Figure 2-2 compares the distribution of hours worked from the Washington State administrative data with student self-reports of hours worked obtained by the National Center for Educational Statistics (NCES) for the 2003–2004 beginning postsecondary students attending public two-year colleges nationally and for the Western region, which includes Washington State (the NCES data is not reported by state). The student self-reports from the Western region and administrative data from Washington State are almost identical in finding that about 27% of students do not work. However, when we compare self-reports versus administrative reports of hours worked, self-reports of hours worked are much higher compared with the UI records in Washington. For example, 25% of the two-year public college students from the national sample and 20% from the Western regional sample claim to be working 40 hours per week or more, while, according to the UI data, only 7% of the students from Washington State worked 40 hours or more per week while they were enrolled at the WSBCTS.

There may be several reasons for the discrepancy between the self-reports and administrative data. It may be the case that students tend to overestimate hours worked. It is also possible that the UI data underestimates hours worked by excluding too many categories of employment. However, this is unlikely because the UI data and the self-reports are very similar when it comes to the percentage of students that report being employed; the two datasets diverge only when it comes to hours worked. Another possible explanation for the discrepancy is that students in Washington State are different from students from students in other U.S. states, or even from students in other states in the Western region. In particular, while in the NCES data 30% to 36% of the national and regional samples included minority students (black or Hispanic), only 11% of the students in the Washington State data belong to these minority groups. At the same time, the differences between the Washington Sample and the sample from the Regional Public 2 year colleges seem too big to be simply explained by sample differences or differences in the coverage of employment and suggest significant reporting bias.

Figure 2-2: Comparison of Self-Reports Versus Administrative Records of Hours Worked



Sources: Author calculations using National Center for Education Statistics, Beginning Postsecondary Sample and WSBCTS matched transcript and Washington State UI data
Notes: *National* refers to the national sample of students attending public two-year colleges during 2003–2004, obtained from the National Center for Education Statistics' (NCES) sample of beginning postsecondary students. *Regional* refers to the NCES sample for the Western states, which includes Washington State (the NCES data is not available by state). *WA sample* is based on administrative data obtained from Washington State UI records. The WA analysis sample includes the additional restrictions.

Another important aspect of community college students' employment is the type of jobs students work at. While various hypothesis about the possible benefits or harms of student employment are based on assumptions about the kinds of jobs that students hold, it has been impossible in the past to provide information about the industries in which community college students are generally employed without access to administrative data.

Table 2-1: Industry of Employment in Quarter 1 and Quarter 26, Employed Students Only

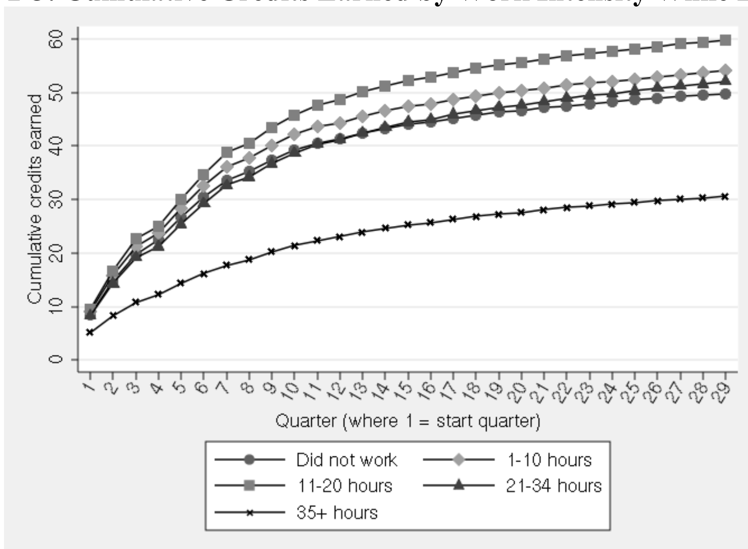
Industry of Employment	Percent of Employed Students, Q1	Percent of Employed Students, Q26
Retail Trade	23.40%	14.20%
Accommodation and Food Services	18.50%	8.70%
Healthcare and Social Assistance	10.10%	14.70%
Construction	8.00%	10.40%
Manufacturing	7.10%	9.30%
Administrative and Support and Waste Management and Remediation Services	5.10%	6.20%
Other Services	4.90%	4.30%
Public Administration	2.90%	4.80%
Educational Services	2.90%	4.90%
Arts, Entertainment, and Recreation	2.60%	2.20%
Wholesale Trade	2.50%	4.00%
Professional Scientific and Technical Services	2.30%	4.10%
Real Estate Rental and Leasing	2.20%	1.90%
Transportation and Warehousing	2.20%	3.20%
Finance and Insurance	2.00%	4.00%
Information	1.70%	2.20%
Agriculture, Forestry, Fishing and Hunting	1.40%	1.10%

Source: Author's calculations using WSBCTC data and matched employment data from Unemployment Insurance records.
Notes: The sample includes all first-time freshmen who enrolled at a Washington State community or technical college in the fall of 2001, were at least partially state funded, had a valid social security number, were not international students, and indicated workforce intent or intent to transfer to a four-year institution.

Table 2-1 includes the breakdown of students' industry of employment during the first quarter of enrollment as well as 26 quarters (5 years) after initial enrollment. The first column indicates that during the first quarter of enrollment, the most common industries that the students are employed in are "retail" and "accommodation and food services;" these industries jointly hire 42% of all working students. "Health care and social assistance" follows these two industries. By the 26th quarter after initial enrollment, most students have exited college, yet still a substantial number of students work in retail trade and accommodation and food services industries. While the proportion that continue to work in these industries is halved compared to the first quarter of enrollment, these industries still constitute the most common industries of employment, only second to "health care and social assistance." More importantly for this analysis, the administrative data on students' industry of employment during the first quarter suggests that the most common jobs that community college students hold are not likely to contribute to the students' development of skills or college achievement.

Figure 2-3 shows how credit accumulation over time varies by students' work intensity during the first semester. Similar to any other descriptive associations between students' intensity of employment and academic outcomes, this descriptive information should not be interpreted causally. Rather, these associations reveal how failing to account for differences among students could lead to the same incorrect conclusions that are found in other descriptive studies. As is suggested by Figure 2-3, students who work moderately while enrolled, between 11 to 20 hours per week, have the highest credit accumulation over time, and students who work 35 hours per week or more have the worst outcomes for credit accumulation over time. Table 2-2, which shows students' demographic characteristics by work intensity, provides evidence to support that students who work moderate hours (11–20 per week) are positively selected, and students who work full time (35 hours per week or more) are negatively selected. In particular, students who work moderate hours are much younger and are less likely to be from low-SES families compared with students who work full time. Because of this, it is very possible that the previous findings in the descriptive literature that suggest that working moderately improves student outcomes are at least partly driven by the positive preexisting characteristics of these students, while the reverse may be true for students who work long hours. It is therefore important to separate the effects of employment from the effects of preexisting student characteristics that jointly determine employment intensity and academic achievement.

Figure 2-3: Cumulative Credits Earned by Work Intensity While Enrolled



Source: Author's calculations using WSBCTC data and matched employment data from Unemployment Insurance records.
Notes: The Sample includes all first-time freshmen who enrolled at a Washington State community or technical college in the fall of 2001, were at least partially state funded, had a valid social security number, were not international students, and indicated workforce intent or intent to transfer to a four-year institution.

Table 2-2: Demographic Characteristics by Work Intensity

Weekly Hours Worked	No Work	1 to 10	11 to 20	21 to 34	35+
Male	51%	51%	46%	45%	58%
Low SES	46%	41%	37%	41%	44%
No High school Diploma	9%	7%	5%	4%	6%
GED only	7%	5%	3%	4%	5%
African American	6%	6%	4%	4%	5%
Latino	8%	9%	8%	9%	12%
Average Age	27	23	22	23	28

Source: Author's calculations using WSBCTC data and matched employment data from Unemployment Insurance records.
Notes: The Sample includes all first-time freshmen who enrolled at a Washington State community or technical college in the fall of 2001, were at least partially state funded, had a valid social security number, were not international students, and indicated workforce intent or intent to transfer to a four-year institution.

2.4. Methodology

The simplest way to estimate the effect of hours worked on academic or labor market outcomes would be to compare the outcomes of students who worked at different levels of intensity, controlling for observed differences among them. The problem with such an approach is that there may be unobserved preexisting differences among students who work at different intensities. For example, more motivated students may be more likely to work longer hours while in school and are also less likely to have positive academic outcomes. To overcome the bias created by the endogeneity of work intensity, I use two different identification strategies. First, I will use an individual fixed effects identification strategy that relies on the within-student-variation of hours worked across quarters to identify the effect of work intensity on academic outcomes. Second, I will use an instrumental variable difference-in-differences strategy that compares the fall versus winter academic outcomes of students who work in retail versus other jobs, taking advantage of the fact that the fall quarter coincides with the holiday shopping season and creates an exogenous supply of work for students that work in the retail industry.

I use two outcomes for which quarterly data is available: GPA and credits earned. Although previous quasi-experimental literature has exclusively focused on the effect of employment on college students' GPA, using GPA as the only outcome may underestimate the effects of employment, because students may respond to an increase in work opportunities by taking fewer courses while maintaining their GPA. This is particularly a problem in a community college sample, where students have great flexibility in the number of classes they take.

2.4.1. Individual Fixed Effect Identification Strategy

In this framework, I compare quarterly GPA and credits earned across quarters for the same student. The individual fixed effect dummy variables control for all time-invariant student characteristics, while dummy variables for each quarter control for any effect of a specific quarter that is shared among all students. In the following model (equation 1), $\mathrm{GPA}_{\mathrm{it}}$ is the grade point average of student *i* at quarter *t*; ρ_{i} indicates a dummy variable for each student, and τ_{t} is a dummy variable for each quarter; $\varepsilon_{\mathrm{it}}$ is the error term. I include $\mathrm{H}_{\mathrm{it}}^2$ in order to allow for a possible non-linear effect of work intensity.

Equation1: Individual Fixed Effects Model:

$$GPA_{it} = \beta_0 H_{it} + \theta H_{it}^2 + \rho_i + \tau_t + \varepsilon_{it}$$

Because I am comparing the outcomes for the same student across different quarters, I am able to control for all observed and unobserved student characteristics (such as ability or motivation) that do not change over time. By including quarter fixed effects, I am also able to control for the shared effects of a specific quarter among students (for example, the effect of a quarter being a student’s first quarter). However, the main shortcoming of this strategy is that it fails to control for student-specific unobserved characteristics or conditions that may change across the first three quarters. This failure could bias the results if students change their work intensity across quarters for reasons that may jointly determine their academic outcomes. For example, students may work less and have worse outcomes during the quarters where they anticipate having difficult coursework, or in a quarter when they become ill or have children. It seems that most conditions that would lead students to work less are likely to also affect their outcomes negatively. As a result we can expect that any resulting bias would introduce a more positive relationship between work intensity, quarterly credits earned, and GPA than would exist in the absence of any bias.

In this model, for a given student, GPA during a quarter in which a student works longer hours is compared with a quarter where the same student works fewer hours. I compare student outcomes across the first three quarters, and therefore I need to limit our sample to students who attempt credits during all of the first three quarters. [9] Unfortunately, because of the high drop-out rates among community college students, this restriction results in losing 45% of the general sample, and 32% of the traditional student sample. This exclusion may also bias the results if most of the effect of working while enrolled is on dropping out of college before students make it to their third quarter.[10]

2.4.2. Instrumental Variable Difference-in-Differences Identification Strategy

Because of the potential bias in using individual fixed effects, I use a second identification strategy that takes advantage of the exogenous increase in the supply of

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[9] When GPA is used as an outcome, the sample is limited to students who have non-missing GPA during the first three quarters, which includes students who have not only attempted but also completed some credits.

[10] Although, if full-time students are only attending college to attend a few classes to update their job skills, then the exclusion would lead to a more homogenous sample. Unfortunately, it is not possible to distinguish between drop-outs that are "affected" by high-intensity work, versus those caused by differences in student intent during the first three quarters.

retail jobs during the holiday shopping months of November and December and the fact that over 19% of all students work in retail jobs while they are enrolled. One possible identification strategy would be to simply use the fall quarter, which includes November and December, as an instrument to predict the increase in hours worked during that quarter. However, a potential problem with such a strategy is that any systematic differences in relative performance of students in the fall quarter that is not attributable to an increase in hours worked would lead to biased estimates. To remedy this, I combine the instrumental variable (IV) estimate with a difference-in-differences (DID) estimation, taking advantage of the fact that we only expect an increase in hours worked for students who are likely to be employed in retail jobs; thus, other students form a natural control group for the analysis. To implement this strategy, I identify students who are likely to work in retail while they are enrolled based on pre-enrollment employment in retail jobs. Fortunately, I have data on students' industry of employment for one year prior to initial college enrollment. Of all students, 21% worked in retail jobs the quarter before enrollment, and the majority of them, (78%) continued to work in retail jobs after they enrolled in college (during the fall quarter). As a result, I can compare the academic outcomes (GPA and credits earned) from the fall quarter versus the winter quarter for students who are more likely versus students who are less likely to work in retail based on their pre-college association with retail jobs. As illustrated in the reduced form equation below, the DID strategy compares the fall and winter academic performance (as measured by GPA and credits earned) of students who are likely to work in retail compared with all other students.

$$y_{it} = \alpha + \beta(Retail \times Fall) + \gamma Fall + \delta Retail + \theta X_i + \varepsilon_{it}$$

In the equation above, *Retail* $\times$ *Fall* is an interaction term that is 1 for students who worked in retail the quarter prior to college entry during the fall quarter. *Retail* and *Fall* are the main effects of pre-college employment in the retail industry and the fall quarter; and X_i is a vector of covariates including age, age squared, race, SES, sex, prior education, family status, an indicator for missing covariates, as well as an indicator for whether the student was employed in the summer prior to college entry). In addition to reporting the reduced form, I also estimate the effect of hours worked (rather than the effect of being a retail associated student during the fall quarter) using the following two-stage model.

First Stage:

$$H_{it} = \alpha + \pi(Retail \times Fall) + \gamma Fall + \delta Retail + \theta X_i + \varepsilon_{it}$$

Second Stage:

$$y_{it} = \Omega + \beta\widehat{H}_{it} + \vartheta Fall + \sigma Retail + \varphi X_i + \varepsilon_{it}$$

The identifying assumption is that (1) the interaction between the fall quarter and being associated with retail jobs is correlated with hours worked, and (2) the interaction between the fall quarter and retail association only affects the academic outcomes through its effect on hours worked.

The first assumption is testable. Table R2 shows the "first stage" results and finds that after controlling for the fall quarter, for whether or not the student worked in retail prior to enrollment, and for a host of student background characteristics (including age, age squared, race, SES, sex, prior education, family status, an indicator for missing covariates, as well as an indicator for whether the student was employed in the summer prior to college entry), there is a significant relationship between the interaction term and hours worked. Being associated with retail in the fall quarter leads to 1.36 more hours worked per week, which is an 11% increase in time spent working. The second assumption is not directly testable; however, in this context it is very plausible to hold because we do not expect there to be a mechanism outside of an increase in hours worked to affect the relative difference in performance of retail-associated students during the fall quarter versus the winter quarter.

2.5. Results

Table 2-3 shows the main estimation results using the individual fixed effects identification strategy, and Table 2-3 includes results from the difference-in-differences estimates. When considering the effects of hours worked on GPA, both identification strategies find small negative effects of an increase in hours worked on GPA. The results for the effect of work intensity on credits earned are more ambiguous, and given that the previous quasi-experimental literature has not examined the effects of student employment on credits earned, it is impossible to put these estimates into context.

2.5.1. Estimates of the Effect of Work Intensity from the Individual Fixed Effects Identification

According to the results using individual fixed effects identification, a one-hour per week increase in employment reduces quarterly GPA by 0.0046 points. Given that the effects are linear; this means that if a student goes from not working to working 10 hours per week, she can expect a decrease of only 0.046 points in her GPA. As Table 2-3 shows, the individual fixed effects model also finds a small, negative, but statistically significant effect of an increase in employment on credits earned. The point estimates from this model suggest that a one-hour increase in employment per week reduces credits earned by -0.065 credits, or a loss of -0.65 or slightly more than half a credit for working an additional 10 hours. Using this model, we can only speculate about the effect of increasing work by up to about 10 hours, because we do not have adequate within-student-variation in hours worked for more than 10 hours; because only 17% of students increase working work hours by more than 10 hours per week, I do not speculate about the effects of increases in work intensities that exceed the one to 10 hour per week range. I also note that within this range, I do not find any non-linearities in increases in hours worked which is indicated by the fact that the coefficient on the squatted term of hours worked approximates zero.

Table 2-3: Individual Fixed Effect Estimates of the Effect Hours Worked While Enrolled on Credits Earned and GPA

OUTCOMES	*Dependent Variable: Quarterly Credits Earned*			*Dependent Variable: Quarterly GPA*		
Weekly Hours Worked	0.0150**	-0.0281***	-0.0650***	-0.0105***	-0.00538***	-0.00465***
	(0.00655)	(0.00664)	(0.0103)	(0.00100)	(0.00101)	(0.00167)
Weekly Hours Worked Squared	-0.00211***	-0.000916***	0.000339	0.000268***	0.000118***	1.09e-05
	(0.000171)	(0.000174)	(0.000246)	(2.66e-05)	(2.66e-05)	(3.98e-05)
Includes Covariates		**X**			**X**	
Includes Individual Fixed Effects			**X**			**X**
Observations	35,235	35,235	35,235	32,465	32,465	32,465
R-squared	0.030	0.063	0.688	0.020	0.072	0.679

Source: Author's calculations using WSBCTC data and matched employment data from Unemployment Insurance records.
Notes: Covariates include age, age squared, race, SES, sex, prior education, family status, as well as an indicator for missing covariates. The sample includes all first-time freshmen who enrolled at a Washington State community or technical college in the fall of 2001, who were at least partially state funded, had a valid social security number, were not an international student, and indicated workforce intent or intent to transfer to a four-year institution. For this table, the sample is limited to students who attempted some credits during the first three quarters of entry. For the GPA analysis, the sample is further limited to students who have non-missing GPA in all the three quarters. Mean quarterly credits earned for the sample is 11.9 (SD: 6.12); mean quarterly GPA is 2.87 (SD: 0.895874). Robust standard errors are in parenthesis; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$; Observations are student-quarter.

2.5.2. Estimates of Effect of Work Intensity using the DID-IV Model

Table 2-4 shows the results from the DID-IV model using the main sample and includes the first and the second stage equations. As discussed earlier, the first stage estimates show how well the interaction of association with retail work and the fall quarter together predicts increases in hours worked over and above either the effect of retail association or the fall quarter. The top panel in Table 2-4 shows the "first stage" estimates of the effect of being a retail-associated student (based on pre-college employment) during the fall quarter (October, November, and December, which includes the holiday shopping season). Being a retail-associated student during the fall quarter significantly increases hours worked, after controlling for retail association and the quarter of employment. The second model adds in students' demographic characteristics and an indicator for whether or not the student was employed the quarter before enrollment). As mentioned earlier, the first stage indicates an increase of 1.36 hours per week of work or 11 percentage points and is estimated with small standard errors.

The second stage, which is shown in the bottom panel of Table 2-4, is the effect of this exogenous increase in hours worked on GPA and credits earned. Although the second stage results are not significant for either GPA or for credits earned, the confidence intervals for the effects on GPA are small enough to reveal important information. The point estimates of -0.028 suggest that a one-hour-per-week increase in students' employment lowers students' GPA by -0.028 points and are very similar to the point estimates found by Kaenkoski and Pabilonia. The confidence interval from the DID estimates easily rejects the point estimates Stinebrickner and Stinebrickner (2003) find in their Barea college sample.

By contrast, the confidence intervals on the effect of hours worked on credits earned using the DID-IV model results are large and do not allow for any useful conclusion about the effect size. The standard errors suggest that the effect could fall between -0.118 and 0.209. Because of this large confidence interval and given that previous studies have not estimated the effects of working on credits earned, the DID model does not contribute to our understanding of the effects of term-time employment on earning credits.

Table 2-4: Difference in Differences Estimates of the Effect of Being a Retail Associated Student during the Fall Quarter

"FIRST STAGE"	Dependent Variable: Weekly Hours Worked					
Retail*Fall	1.364***	1.364***				
	(0.398)	(0.389)				
Includes Covariates		**X**				
Observations	28,784	28,784				
R-squared	0.045	0.229				
OUTCOMES	*Dependent Variable: Quarterly Credits*			*Dependent Variable: Quarterly GPA*		
	Reduced Form		IV_DID	Reduced Form		IV_DID
Retail*Fall	0.249	0.249		-0.0372	-0.0373	
	(0.183)	(0.182)		(0.0301)	(0.0296)	
Weekly Hours Worked			0.182			-0.0286
			(0.150)			(0.0242)
Includes Covariates		**X**	**X**		**X**	**X**
Observations	28,784	28,784	28,784	25,880	25,880	25,880
R-squared	0.006	0.047		0.012	0.059	

Source: Author's calculations using WSBCTC data and matched employment data from Unemployment Insurance records.
Notes: In addition to key interaction term (Retail*Fall), all regressions include the main effects of association with a retail job and the fall quarter. Models with covariates also include age, age squared, race, SES, sex, prior education, family status, an indicator for missing covariates, as well as an indicator for whether the student was employed in the summer prior to college entry.
The sample includes all first-time freshmen who enrolled at a Washington State community or technical college in the fall of 2001, who were at least partially state funded, had a valid social security number, were not international students, and indicated workforce intent or intent to transfer to a four-year institution. For Table 2-4, the sample is limited to students who have attempted some credits during the first two quarters of entry. For the GPA analysis, the sample is further limited to students who have non-missing GPA in all the three quarters.
Robust standard errors are in parenthesis; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
Mean quarterly credits earned for the sample is 11.41 (SD: 6.31); mean quarterly GPA is 2.83 (SD: 0.94)

2.5.3. Estimating the Effect of Work Intensity for the Subgroup of "Traditional" Students

Our general sample includes a variety of community college students that represent different age groups and includes students who have academic or vocational intent. It could be argued that older students and students whose intent is to pursue a vocational degree may benefit more or be harmed less from working while studying when compared with traditional students who are younger and who intend to earn an academic credential or transfer to a four-year college. In order to test whether or not these results are robust for a more traditional group of students, I estimate both the individual fixed effects model and the IV-DID model for a limited sample that includes students who are 20 years old or younger and only those who declare an intent to earn an academic credential or transfer upon initial enrollment. Table 2-5 show the individual fixed effects results for the sample of traditional students and table 2-5 shows the IV-DID results for the same sample. As the tables indicate, the results from the limited sample are almost identical to the results from the general sample. This indicates that the results from our general sample are not driven by students who are older and have vocational intent and that the results are similar for more "traditional" students.

Table 2-5: Individual Fixed Effect Estimates of the Effect Hours Worked for "Traditional Students"

OUTCOMES	*Dependent Variable: Quarterly Credits Earned*			*Dependent Variable: Quarterly GPA*		
Weekly Hours Worked	0.0120*	-0.0390***	-0.0578***	-0.0119***	-0.00518***	-0.00508***
	(0.00704)	(0.00716)	(0.0113)	(0.00112)	(0.00112)	(0.00188)
Weekly Hours Worked Squared	-0.00207***	-0.000697***	0.000359	0.000300***	0.000107***	6.54e-06
	(0.000182)	(0.000186)	(0.000264)	(2.95e-05)	(2.94e-05)	(4.43e-05)
Includes Covariates	X			X		
Includes Individual Fixed Effects		X			X	
Observations	27,204	27,204	27,204	25,078	25,078	25,078
R-squared	0.034	0.072	0.687	0.020	0.084	0.678

Source: Author's calculations using WSBCTC data and matched employment data from Unemployment Insurance records.
Notes: The "Young Transfer Sample" is also limited to students who are 20 years or younger and have indicated an intent to transfer to a four year institution. Covariates include age, age squared, race, SES, sex, prior education, family status, as well as an indicator for missing covariates.
The sample includes all first-time freshmen who enrolled at a Washington State community or technical college in the fall of 2001, who were at least partially state funded, had a valid social security number, were not an international student, and indicated workforce intent or intent to transfer to a four-year institution. For this table, the sample is limited to students who have attempted some credits during the first three quarters of entry. For the GPA analysis, the sample is further limited to students who have non-missing GPA in all the three quarters.
Mean quarterly credits earned for the sample is 11.86 (SD: 5.64); mean quarterly GPA is 2.88 (SD: 0.88)
Robust standard errors are in parenthesis; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$; Observations are student-quarter.

Table 2-6: Difference in Differences Estimates of the Effect of Being a Retail Associated Student during the Fall Quarter for "Traditional Students"

"FIRST STAGE"	Dependent Variable: Weekly Hours Worked					
Retail*Fall	1.595***	1.595***				
	(0.459)	(0.448)				
Includes Covariates		X				
Observations	16,086	16,086				
R-squared	0.071	0.222				
OUTCOMES	*Dependent Variable: Quarterly Credits*			*Dependent Variable: Quarterly GPA*		
	Reduced Form		IV_DID	Reduced Form		IV_DID
Retail*Fall	0.0148	0.0148		-0.0392	-0.0383	
	(0.201)	(0.200)		(0.0364)	(0.0360)	
Weekly Hours Worked			0.182			-0.0286
			(0.150)			(0.0242)
Includes Covariates		X	X		X	X
Observations	16,086	16,086	16,086	15,609	15,609	15,609
R-squared	0.009	0.016	0.012	0.010	0.029	

Source: Author's calculations using WSBCTC data and matched employment data from Unemployment Insurance records.
Notes: In addition to key interaction term (Retail*Fall), all regressions include the main effects of Association with a retail job, and the fall quarter. Models with covariates also include age, age squared, race, SES, sex, prior education, family status, an indicator for missing covariates, as well as an indicator for whether the student was employed in the summer prior to college entry.
The sample includes all first-time freshmen who enrolled at a Washington State community or technical college in the fall of 2001, who were at least partially state funded, had a valid social security number, were not international students, and indicated workforce intent or intent to transfer to a four-year institution. For this table, the sample is limited to students who have attempted some credits during the first two quarters of entry. For the GPA analysis, the sample is further limited to students who have non-missing GPA in all the three quarters.
Robust standard errors are in parenthesis; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$
Mean quarterly credits earned for the sample is 12.22 (SD: 5.22); mean quarterly GPA is 2.73 (SD: 0.92)

The results from both models highlight the fact that small changes in hours worked (fewer than 10 hours) only lead to small reductions in GPA. The fact that both models reject the large negative effects found by Stinebrickner and Stinebrickner (2003) indicates that the estimates for students at Berea College are not generalizable to students who attend a community college, at least for those in Washington State. By contrast, when considering quarterly credits earned as the outcome, because of the large standard errors in the IV-DID model, it is impossible to make firm conclusions about the effect of increases in term-time employment on credit accumulation.

In comparing the rigor of the methodology in each model, while the estimates from the individual fixed effects model are more precise, the DID-IV model has much higher internal validity. The individual fixed effect model has several potential shortcomings that can bias the estimates. First, this model only includes students who enrolled in college for the first consecutive quarters, and thus, to the degree that increasing work results in a student dropping or stopping out, the model does not capture negative effects. Second, most of the endogenous reasons that could cause students to work less—for example, changes in a student's personal situation, such as giving birth or health issues—would also negatively affect academic outcomes, and thus could cause an underestimation of the negative effects of working. Finally, students may reduce employment during the quarters that they expect to have more difficult coursework, which might again cause an underestimation of the negative effects of work. In contrast, my DID estimates have greater internal validity and overcome all of the issues discussed above, but they are estimated less precisely. However, even with the larger confidence intervals, the DID-IV model still rejects the large and negative estimates of the magnitude suggested by Stinebrickner and Stinebrickner (2003), and thus I can conclude that even according to these imprecise estimates, the large negative effects of term-time employment that were suggested by Stinebrickner and Stinebrickner are easily rejected for this sample.

2.6. Discussion

This study is one of the first to examine the causal link between community college students' employment while enrolled on academic outcomes. I take advantage of a rare administrative dataset from Washington State that combines transcript records of the students who initially enrolled in one of Washington's community and technical colleges during the 2001–2002 academic year with employment data, which includes quarterly hours worked, from Washington State Unemployment Insurance records. I use an individual fixed effects model, as well as an instrumental variable difference-in-differences identification strategy, to examine how term-time employment affects students' quarterly GPA and credit accumulation.

My findings on GPA suggest small negative effects, and specifically my IV-DID estimates are strikingly similar to the findings of Kalenkoski and Pabilonia (2010), the only other study in the literature that examines the consequences of employment for community college students separately. Unfortunately, there are no other studies that examine the effects of work intensity on first-semester credits earned for community college students; however, the results from my IV-DID model closely approximate the positive point estimates found by Scott-Clayton (2011). These findings suggest that moderate increases in hours worked (fewer than 10 hours per week) have very small negative effects on GPA but may increase credit accumulation by reducing credit constraints that may have prevented students from taking additional courses.

Like any other empirical study, this study is not without limitations. The results from the two models diverge when we consider effects of term-time employment on credit accumulation, but given that the samples of students I use for each identification strategy is different, somewhat different results would be expected. In particular, the individual fixed effects model is limited to using a more restricted sample of students who are enrolled for three consecutive quarters and thus have greater institutional attachment compared to the DID sample which is restricted to students who are required to be enrolled for only the first two consecutive quarters. In addition, as explained in detail in the results section, the individual fixed effects includes several threats to internal validity most importantly that within student variation in hours worked maybe for endogenous reasons that could affect the outcome, or students may adjust how much they work according to the expected difficulty of the coursework. The IV-DID model overcomes all of the shortcomings of the individual fixed effects model but is estimated with less precision. The estimates resulting from these two strategies balance precision with internal validity. Even though the IV-DID estimates are not statistically significant, the confidence intervals are tight enough that we can easily reject the large negative effects that are suggested by Stinebrickner and Stinebrickner(2003), which is the only natural experiment of the effects of college student employment.

Taken together, my estimates suggest that the large negative effects of moderate increases in hours worked found in the Berea college sample are not present for community college students; using both methods, my confidence intervals easily reject Stinebrickner and Stinebrickner's (2003) findings. Instead, I find that a moderate increase of one to 10 hours of work per week has very small negative effects on GPA and may have positive effects on credits earned. Unfortunately, because of data limitations I am not able to examine the effects on other outcomes such as drop-out or graduation, and it is possible that the potentially large negative effects that Scott-Clayton (2011) finds for the federal work study for such outcomes, also exist for other types of employment.

Chapter 3

How Much Does a Community College Education Pay?[11]

3.1. Introduction

As community colleges continue to enroll a large proportion of the nation's undergraduate population, an accurate estimate of the value of a community college education is essential. Thirty-seven percent of students who enrolled in a degree-granting college in the fall of 2008 did so at a two-year institution.[12] Furthermore, for many of the low-income and minority students in the United States, community colleges provide a relatively affordable opportunity to gain the skills needed to obtain family-supporting jobs (Hoachlander, Sikora, & Horn, 2003; Levin, 2007). Currently, the literature on the labor market value of community college credentials is relatively limited; studies on the labor market returns to credentials often focus on the returns to four-year degrees. For example, a recent report from the Center on Education and the Workforce at Georgetown University examined how college majors affect the earnings

[11] This chapter describes joint work with Madeline J. Weiss of CCRC and a related report will be released as a CCRC working paper.

[12] From published data from the Integrated Postsecondary Data System (IPEDS), obtained from http://nces.ed.gov/programs/digest/d10/tables/dt10_195.asp

of students who earn bachelor's degrees (Carnevale, Strohl, & Melton, 2011). But the majors examined in the report are different from the fields of study commonly offered by community colleges, and therefore the report doesn't provide much useful information for a community college trying to determine its program offerings, or for a community college student trying to decide on a career path.

Unlike most four-year colleges, community colleges offer a diverse mix of credentials to students, including liberal arts and occupational associate degrees, as well as certificates of different lengths. In particular, some certificates require less than a year of full-time study to complete, while other certificates require a year of full-time study or more (Bosworth, 2010). We refer to these as short-term certificates and long-term certificates, respectively.[13] In addition, the mix of credential types awarded at community colleges greatly varies across the nation and has also changed over time even within states. For example, in 2010, only 0.1 percent of credentials awarded in New York were short-term certificates, while in Kentucky 62.9 percent of the credentials awarded were short-term certificates. At the same time, there has also been a great shift in the composition of credential type within a given state over time, mostly in favor of offering more short-term certificates. Between the years 2000 and 2010 the number of short-term certificates awarded increased by 151 percent nationally, increasing the share of sub-baccalaureate credentials that are short-term certificates from

[13] In some states, short-term certificates and long-term certificates have different formal names. For example, in Kentucky, long-term certificates are called "diplomas" while short-term certificates are referred to as simply "certificates."

16 percent to 25 percent in only a decade.[14] As short-term certificates become an ever more important part of the picture at community colleges, it is essential to assess this trend and its implications for students. Do these short-term certificates lead to increases in wages and employment, and if so, how do these increases compare to those of longer term credentials?

This study attempts to contribute to the very limited evidence on the labor market value of different types of community college credentials by specifically addressing the following research questions:

1. To what extent do sub-baccalaureate credentials (short-term certificates, long-term certificates, and associate degrees) increase the wages of students who earn them?
2. What is the effect of these credentials on increasing the likelihood that students will be employed or, if employed, work more hours?
3. How do the wage returns to credentials vary by field of study?

We use data from the 2001–2002 cohort of first-time students in Washington State, tracked through the 2008–2009 academic year, and rely on an individual fixed effects identification strategy and examine the labor market returns to a specific type of community college credential which also includes both the value of the credits students

[14] Authors' calculations using IPEDS data. Based on public, degree-offering, primarily postsecondary, Title IV-eligible institutions with at least 90 percent of credentials awarded are those awarded at the sub-baccalaureate level.

earn when they complete a specific credential and the value of that specific diploma over and above the value of the credits earned (referred to as diploma effects or sheepskin effects).. Because we obtain our administrative data from community college transcript records, unlike most previous studies on the topic, we are unable to compare the value of credentials to earning a high school diploma, and instead we estimate the value of earning a specific credential to showing-up in college and earning some credits but never earning credential.

Our findings suggest that there is great variation in the labor market value of different credential levels, and that there is even greater variation by field of credential. While associate degrees and long-term certificates increase wages, on the likelihood of being employed, and hours worked, we find minimal or no positive effects for short-term certificates. We also find that associate degrees tend to have higher returns than long-term certificates within a given field.

3.2. Previous Empirical Literature

A vast majority of the literature on the returns to schooling has focused on the returns to education at high school and four-year colleges (for a review of this literature, see Card, 1999, 2001). By contrast, there is somewhat limited research on the returns to community college education (Belfield & Bailey, 2011).

The existing literature on the returns to community college schooling is mostly based on Mincerian equations using cross-sectional data. These studies generally compare earnings of students with different amounts of community college education with students who only have a high school diploma,, while controlling for years of work experience and observed student characteristics (Grubb, 1993; Grubb, 1997; Kerckhoff & Bell, 1998; Jacobson & Mokher, 2009; Monk-Turner, 1994; Kane & Rouse, 1995; Leigh & Gill, 1997; Bailey, Kienzl, & Marcotte, 2004). This literature is plagued by the problem of selection bias—that is, the fact that higher ability and more motivated students tend to have higher college attainment and also tend to have higher earnings. Given that the main “unobservable” difference between more educated and less educated students that may also affect later life earnings is ability, studies that have included proxies for ability provide more credible estimates. For example, Kerckhoff and Bell (1998) were able to control for several measures of high school achievement (grade point average and scores on both mathematics and reading achievement tests) as well as the type of high school program (academic or vocational) attended, approximating controls for ability and intent, along with labor force experience. Similarly, Kane and Rouse (1995) included test scores as a proxy for ability. In a review of six studies that attempted to control for differences in students’ ability using proxy measures, Kane and Rouse found that the returns to a year of community college credits leads to a 5–8 percent increase in annual earnings over and above only having a high school diploma (Kane & Rouse, 1995).

Most commonly, studies that have estimated returns to credentials have examined the returns to associate degrees, but less frequently have studies also included specific information on the returns to certificates. In their review of the literature, Bailey and Belfield (2011) summarized the evidence on the returns to associate degrees as an average of a 13 percent increase in earnings for men and a 22 percent increase in earnings for women over and above having a high school diploma.[15] A few studies also examined the returns to certificates. Bailey et al. (2004) compared annual earnings for students who had attained a certificate to high school graduates. They found no returns to earning a certificate for men, but higher returns to earning a certificate compared with no postsecondary education for women. Furthermore, in two different studies, one using the National Longitudinal Study of 1972 and the other using Survey of Income and Program Participation (SIPP) data, Grubb found mixed evidence on whether or not certificates increased earnings (Grubb, 1997; Grubb, 2002a; Grubb, 2002b). Kerckhoff and Bell (1998), using data from the National Center for Education Statistics (High School and Beyond), found that students who earned licenses and certificates had wages that were comparable to those who earned associate degrees and higher than students who had only earned a high school diploma. Neither Bailey et al., Kerckhoff and Bell, nor Grubb, however, distinguished between the returns to short-term and long-term certificates.

Only one rigorous study (Jepsen, Troske, & Coomes, 2011) has distinguished between the returns to short-term and long-term certificates, in addition to associate

[15] In these studies the returns to a credential includes both the value of the credits a students has earned as well as the value of the diploma over and above the value of credits (sheepskin effects). Some studies also report the value of credits earned and the sheepskin effects in addition to the overall effect mentioned above.

degrees.[16] By employing individual fixed effects, the authors were able to control for all time-invariant observable and unobservable differences among students. Using data from Kentucky State, the authors found that associate degrees and long-term certificates on average have quarterly earnings returns of nearly $2,000 for women and $1,500 for men, while short-term certificates had minimal returns for both men and women.

Another important question that has received limited attention from researchers is whether there is variation in returns to credits or credentials across different fields of study. There is evidence that student *perceptions* of the likely returns to a particular field of study influences their choice of field of study to begin with (Stuart, 2009; Arcidiacono, Hotz, & Kang, 2010), highlighting the importance of understanding how returns to credentials vary across fields. Grubb's research was among the first to examine the returns to sub-baccalaureate credentials by field of study. Grubb (2002a) found a large degree of variation across fields of study, generally finding that the largest positive returns were to health-related credentials, especially for women, and engineering and computer fields for men. Because of small sample sizes, Grubb (1997) was not able to examine the returns to certificates by field of study with confidence. By contrast, taking advantage of the large sample sizes of their administrative data, Jepsen et al. (2011) examined returns to associate degrees, long-term certificates, and short-term certificates across fields of study. While their analysis is the first analysis of

[16] Several purely descriptive studies have distinguished between short-term and long-term certificates, however; see Bosworth (2010) for a review of this literature.

certificates of different lengths by field of study, their categories used to examine fields of study are (like most other studies that examine fields of study) too broad to reflect the real distinctions typically made at community colleges. For example, the authors do not distinguish between nursing and other allied health programs. Thus the authors found high returns to associate degrees in "health" and in "vocational" fields and minimal or negative returns to associate degrees in "business," "services," and "humanities."

Jacobson, LaLonde, and Sullivan (2005) studied the returns to credits (rather than credentials) by field of study for displaced workers in Washington State. Their study, exploiting a longitudinal dataset that followed students for about four years after initial enrollment, used an individual fixed effect identification that controlled for all time-invariant student characteristics. They found significant positive returns (about 6 percent) to a year of schooling for both men and women after allowing for a post-training adjustment period. However, these positive returns were larger for credits in more technically-oriented fields (which they term "Group 1" credits), while the returns to "Group 2" credits are negative and generally not significant. Unfortunately, the study's external validity may be limited; the study's sample of displaced workers means that these results may not be generalizable to overall returns to sub-baccalaureate education. Also, the distinction between "Group 1" and "Group 2" credits is probably insufficient to understanding the role that field of study plays in returns to schooling, as each category includes a wide variety of very different fields. In particular, "Group 2" classes include everything from academic social sciences and humanities, to business and "less technical vocational tracts," to basic skills and English as a second language (ESL).

A more recent study provides evidence on the influence of field of study in determining earnings after college graduation for a sample of recent high school graduates. Jacobson and Mokher (2009) tracked the 1996 cohort of ninth graders in Florida and found that among those earning a certificate or an associate degree, those with a concentration in a career and technical education (CTE) field had higher earnings in their early-to-mid 20s than those in other concentrations, even after controlling for a rich set of covariates that included high school performance and prior work experience. Moreover, once student characteristics and choice of concentration were taken into account, students who earned certificates had higher post-college earnings than students who earned associate degrees. However, this effect may be related to the fact that students who earned certificates were much more likely to concentrate in a high-return CTE field rather than in a humanities or social science field (Jacobson & Mokher, 2009). Jacobson and Mocker were only able to examine the returns to certificates of one year or longer (long term certificates).

We should note that our study, like the study by Jepsen et al compares students who earn a credential to students who earn some community college credits and no credentials, and thus the interpretation of the results is different from previous cross sectional studies which compare the value of a community college credential to a high school diploma. In comparing our results to the previous cross-sectional studies, it is important to note that our results estimates the value of a credential over and above the average value of credits that students who never earn a credentials earn. Therefore, our estimates of the returns to credentials are lower than they would have been if we had been able to compare our estimates to high school graduates.

Our study uses a similar methodology to those used by both Jepsen et al. (2011) and Jacobson, LaLonde, and Sullivan (2005), estimating the returns to short-term certificates, long-term certificates, and associate degrees in different fields. Our analysis uses Washington State data, allowing for the comparison of previous results to those from Kentucky. Washington State is relatively representative of the national average in terms of the mix of credentials offered and is therefore a good state from which to provide evidence.[17] Additionally, we have a relatively long follow-up period of approximately seven years after initial entry, which is a year and half longer than in the follow-up period for the sample in Kentucky. Another advantage of our data is that the Washington Unemployment Insurance (UI) system is among the few state UI systems that can be linked with postsecondary educational data and also records total hours worked in the quarter and quarterly earnings. Because wages are not always available, many studies examine the returns of schooling or credentials to earnings, which consists of two components: wages that according to economic theory represent workers' skills (more formally referred to as human capital), and quantity of employment (Becker,

[17] The national average mix of sub-baccalaureate credentials in 2010 was 25 percent short-term certificates, 16 percent long-term certificates, and 59 percent associate degrees. Washington is relatively close to these national averages, with 34 percent of credentials awarded in 2010 being short-term certificates, 12 percent long-term certificates, and 54 percent associate degrees. Authors' calculations using data from IPEDS.

1962). However, in this study, we are able to calculate hourly wage rates and therefore examine the returns to wages that result from earning a credential. Finally, by using Classification of Instructional Programs (CIP) code information that is available, we are able to code a more fine-tuned measure of field of study than what has been typically used, so that community colleges can better understand the returns to credentials in different fields.

3.3. Data and Background

3.3.1. Data

Student unit-record data was obtained from the Washington State Board of Community and Technical Colleges (SBCTC). This data contains detailed, de-identified institutional records for all students who attended any of the 34 community and technical colleges in Washington State during the 2001–2002 academic year. For the purposes of this analysis, our sample was further restricted to first-time college students in 2001–2002 (meaning, students with no prior enrollment records, transcript records, or self-reported postsecondary experience).

Student enrollment, transcript, and credential records from the SBCTC were supplemented with matched employment data from Unemployment Insurance (UI) records.[18] Additionally, records were matched with information from the National

[18] Unemployment Insurance records include records from Washington State and the nearby states of Alaska, Idaho, Montana, and Oregon, as well as federal, military, and postal service records.

Student Clearinghouse to determine whether students transferred to four-year institutions or otherwise outside of the Washington community and technical college system. It is important to note a key data limitation: we are unable to track categories of employment that are not recorded in UI data, so some types of employment (such as self-employment and undocumented employment) may not be represented in these data. Washington UI data include both total earnings and total hours worked each quarter, allowing for an analysis of wages in addition to an analysis of earnings.

Our sample was limited to students whose courses were at least partially state-subsidized,[19] had a valid social security number (and thus could be matched with UI records), were not international students, and were between the ages of 17 and 60 at the time they first enrolled. Additionally, since Washington community and technical colleges serve a diverse population that comprises varying intents (including basic skills and continuing education students), we further limited our sample to students who were categorized with either an intent of baccalaureate transfer or to enroll in a career-technical program of study. We further exclude the 7 percent of students who have no wage records during all of the 33 quarters for which we have earnings data available. This initially limits our sample to 37,438 first-time students.

[19] This does *not* refer to the receipt by students of financial aid. Rather, this restriction excludes students who were taking only courses for which the state does not provide any FTE institutional subsidy (e.g., not-for-credit courses, contract-funded courses, or adult basic education or continuing education courses).

Because our identification depends on the change in wages that results from obtaining a community college credential, in our primary analysis (which uses log wages as an outcome), we limit our sample to students who have wage records both prior to enrollment and after exit from the community and technical colleges. This results in a sample of 24,221 students, with a loss of about 35 percent of our initial sample. (About 27 percent of the individuals in this sample are missing any prior wage records and 13 percent are missing any post-exit wage records.) As we explain further in the results section, our estimates are robust to including these students. We use this same primary sample of 24,221 students for our descriptive analyses and for most of our individual fixed effects analyses, but we include a larger sample of students, including those with zero post-college earnings, when we consider the likelihood of employment.

3.3.2. Background on Our Sample

Preexisting differences among students can lead to both a higher likelihood of graduation with a particular credential and higher average earnings. Some of these are observed characteristics (such as gender, age, socioeconomic status,[20] race, and enrollment intensity) and some are unobserved (such as ability and motivation). In developing estimates of the returns to credentials, we attempt to control for both of these using an individual fixed effects methodology, but we first show how observed student

[20] The socioeconomic status (SES) measure used here was developed by CCRC researchers in collaboration with the research staff of the Washington State Board for Community and Technical Colleges (Crosta, Leinbach, & Jenkins, 2006). It sorts students into five SES quintiles and is based on the average SES characteristics in each Census block, including household income, education, and occupation.

characteristics differ for students who end up with different credentials or those who do not earn a credential.

Table 3-1: Student Characteristics, by Type of Credential Ultimately Earned

	None of the following	Short-term certificate	Long-term certificate	Associate degree	Transfer to 4-year institution
Sex					
Female (52%)	44%	54%	62%	55%	53%
Male (48%)	56%	46%	38%	45%	47%
Age at entry					
19 or younger (51%)	45%	37%	39%	70%	74%
20 to 26 (21%)	23%	21%	21%	14%	15%
27 to 45 (22%)	25%	33%	31%	14%	10%
46 or older (6%)	7%	9%	9%	3%	1%
Socioeconomic status					
Top 2 quintiles (37%)	34%	27%	34%	43%	46%
Bottom 2 quintiles (41%)	44%	50%	44%	36%	32%
Race					
White (74%)	73%	70%	76%	80%	77%
African American (5%)	6%	7%	8%	3%	4%
Latino (10%)	11%	8%	5%	7%	7%
Asian or Pacific Islander (7%)	7%	12%	9%	8%	9%
Native American (2%)	2%	1%	1%	1%	1%
Other (2%)	2%	2%	2%	1%	2%
Enrollment intensity in first quarter					
Fewer than 5 credits (19%)	25%	19%	13%	3%	5%
At least 5 but fewer than 12 credits (33%)	35%	31%	29%	23%	28%
At least 12 but fewer than 20 credits (43%)	35%	40%	43%	67%	63%
More than 20 credits (5%)	5%	10%	15%	7%	4%

Table 3-1 shows the demographic and other student characteristics of the students in our sample based on the type of credential ultimately earned by these students within our tracking period of seven years. We see that students who never receive a credential are disproportionately male, while students who earn long-term certificates are disproportionately female. Certificate earners are more likely than others to be older (over the age of 27) and from the bottom SES quintiles, while associate degree earners and students who transfer to baccalaureate institutions are much more likely to be traditional-aged students (age 19 or younger) and from the top SES quintiles.

Initial enrollment intensity also seems to be related to whether or not students earn a credential and what kind of credential students earn. About half of the students in our sample started out taking classes full time (12 or more credits per quarter). More specifically, 19 percent of the sample attempted fewer than five credits in their first quarter; 33 percent attempted at least five but fewer than 12 credits; 43 percent attempted at least 12 but fewer than 20 credits; and 5 percent attempted more than 20 credits.[21] Students who earn an associate degree or transfer are much more likely to begin with a full-time course load, while students who earn a certificate are the most likely of anyone to take substantially more than a full-time load of credits.[22]

Students earned credentials and took classes across a wide range of fields of study. Table 3-2 demonstrates the range of fields of study typical in Washington State

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[21] In Washington State, classes run on the quarter system. That is, there are four quarters during the year (summer, fall, winter, and spring), which roughly correspond with fiscal year quarters. A typical full-time course load might include three traditional classes (about 15 credits) per quarter for three quarters each year, so that a year of full-time study is equivalent to 45 credits. However, a student is considered by the state to be full-time if they take 12 or more credits in a given quarter.

[22] Some occupational programs in Washington are run on a block schedule, where students may take classes in a cohort of five days per week (Monday to Friday) for five to six hours per day, leading to a very high credit load.

community and technical colleges for men and women. The fields of study shown in Table 3-2 are based on students' concentrations—that is, the field of study in which students have attempted most of their college-level credits, as long as they've taken at least three classes or 12 credits within that field of study.[23] About half of the students took classes that were predominantly in the liberal arts (humanities and social science or math and science), while the others half took classes in career–technical fields. There was tremendous variation in the popularity of fields by sex. While general academic liberal arts (humanities and social sciences) is the single most popular concentration for both women and men, there is divergence after that by sex. Mechanics, repair, and welding—a career–technical field—was the second most popular concentration for men, but it ranked near the bottom in popularity for women. Construction was similarly popular for men, but unpopular among women. In contrast, allied health was the third most popular field for females, but ranked in the bottom half of fields of study for males.

[23] Using students' concentrations allows us to single out the field of study in which each student is focusing their coursework, without relying on declared major, which may be unreliable for non-workforce students. See Jenkins and Weiss (2011) for more information about student concentrations in Washington State.

Table 3-2:Fields of Study in Which Students Concentrate

	Females	Males	All
Humanities and social sciences	45%	35%	40%
Math and science	11%	9%	10%
Mechanics, repair, and welding	1%	14%	7%
Information science, communication, and Design	5%	9%	7%
Business and marketing	8%	5%	6%
Allied health	10%	3%	6%
Construction	1%	9%	5%
Cosmetology, culinary, and administrative services	6%	2%	4%
Engineering sciences	1%	6%	3%
Education and childcare	5%	1%	3%
Nursing	5%	1%	3%
Protective services	1%	4%	3%
Transportation	0%	2%	1%
Other CTE/not assigned	1%	1%	1%

Note. Field of concentration refer to the field of study in which a student took the greatest number of credits or classes, with a minimum of 12 quarter credits or 3 classes in that field. Adapted from authors' calculations using student unit-record data for first-time students with workforce or transfer intent who attended any of the 34 community and technical colleges in Washington State during the 2001–2002 academic year.

Before we present the individual fixed effects estimates that attempt to demonstrate a causal link between earning a specific credential type and labor market outcomes, we present two figures showing the trajectory of wages and earnings from a year prior to college entry until about seven years after initial enrollment. The figures present the different trajectories for students who earned different levels of credentials as well as the comparison group of students who took some classes, but did not earn any credentials within seven years after initial enrollment. Figure 3-1 displays the trajectory of earnings and Figure 3-2 displays the trajectory of hourly wages, starting four quarters prior to initial enrollment and up to 28 quarters after initial enrollment.

As both figures highlight, students who earn different types of credentials have very different initial earnings and wages. This is one reason why it is more revealing to examine differences in trajectories rather than differences in levels of earnings. Students who end up obtaining an associate degree start off with among the lowest wages and earnings, only second to students who transfer, but end up having higher earnings and wages compared with any other student group, including those who earn shorter credentials as well as the comparison group (students who enroll in college but who do not earn a credential or transfer within seven years). Students who end up earning a long-term certificate start off with higher earnings than other student groups, perhaps because they tend to include older students and dislocated workers. Students who eventually transfer to a four-year institution start with the lowest wage rates, but their wages and earnings surpasses some of the other groups of students after 29 quarters. In fact, for students who eventually transfer, it seems like even having seven years of data may be inadequate to capture their true increases in wages and earnings; their earnings and wages are increasing more rapidly than the overall trend in the last few quarters. Because this trend suggests that even with seven years of follow-up we may underestimate the returns to transferring, we do not report the coefficient for the effect of transfer in our analysis.

Figure 3-1: Quarterly Trajectory of Earnings, by Eventual Academic Outcome

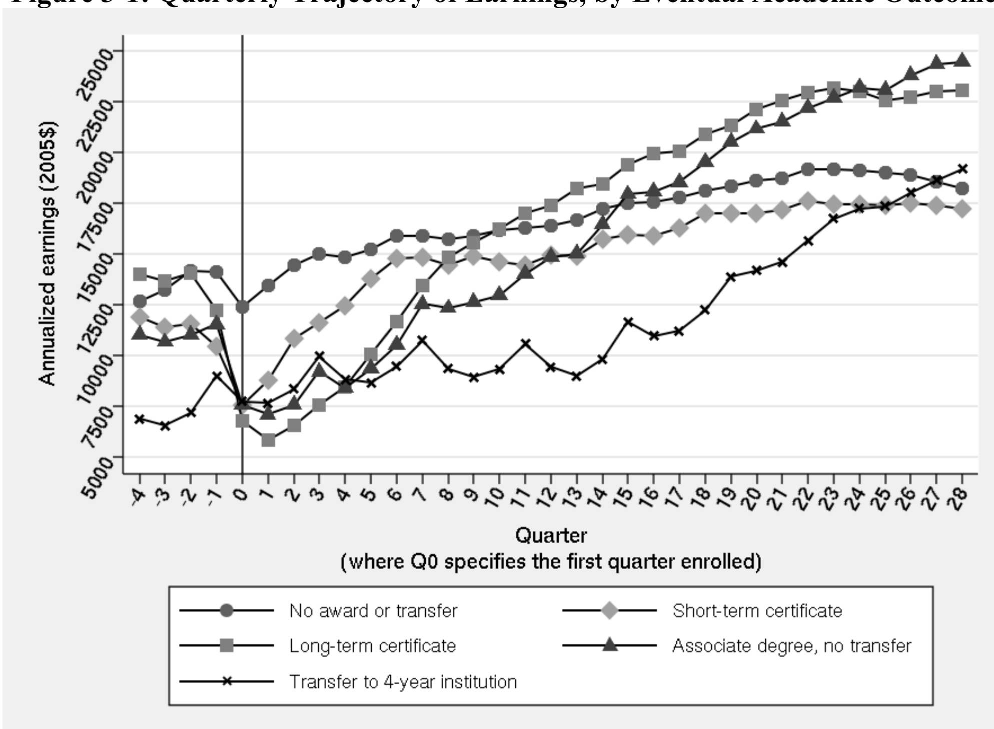
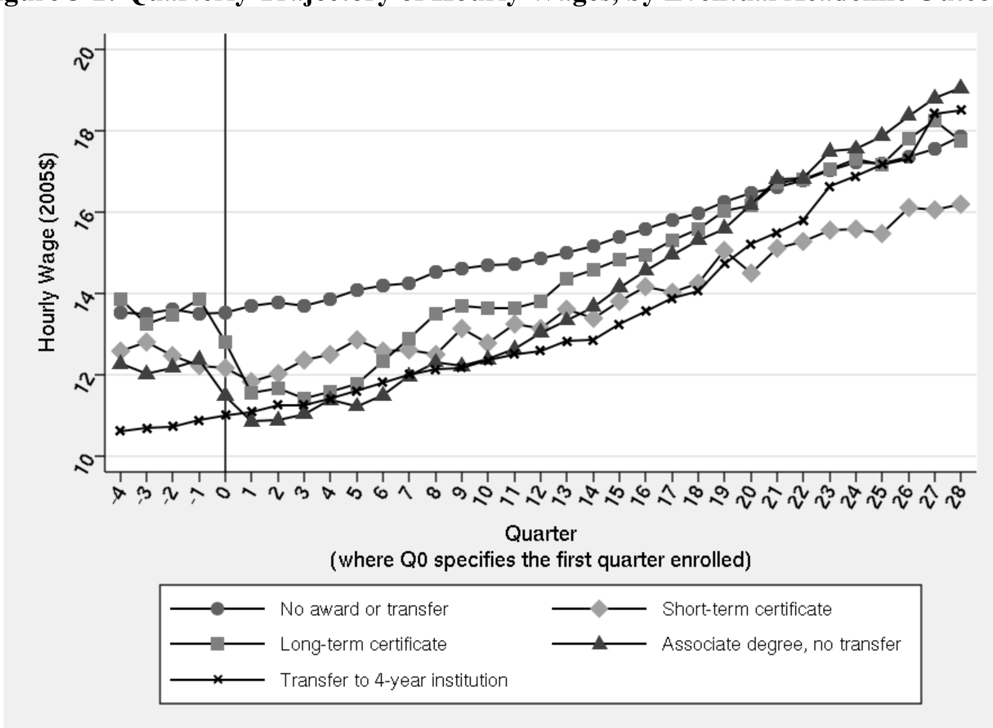


Figure 3-2: Quarterly Trajectory of Hourly Wages, by Eventual Academic Outcome



It is important to note that the comparison group in our study is students who *attended* Washington CTCs but who did not ultimately wind up earning an award. These are students with at least some postsecondary experience—their median number of credits earned over the course of our study is 15 (mean average 29). In contrast, some other studies in the literature (particularly those that use national survey data) include comparisons to high school graduates with no postsecondary experience.

3.4. Methods

In this section, following our main research questions outlined in the introduction, we introduce the equations that we employ in order to answer our three main questions. We first introduce the main equation we use to estimate the average wage increases that result from earning different credentials; we then introduce the equations used to estimate the average employability effects of earning different credentials; and finally introduce the equation used to estimate the wage returns to different credential levels by the field in which the credential is awarded.

3.4.1. Estimating Wage Returns of Earning a Credential

In this section, we examine the average effect of earning different levels of credentials (including short-term certificates, long-term certificates, and associate degrees) on wages. Following studies by Jepsen et al. (2011) and Jacobson, Lalonde and Sullivan (2005), our preferred model is an individual fixed effects model. This model estimates the returns to wages by comparing the trajectory of wages prior to college entry, during college, and after college attendance for students who earn a specific type of credential and for students who enroll but do not earn any credentials in the seven years after initial entry. This method resembles a multiple period difference-in-differences model. Thus, using this methodology, we are able to account for both the observable and unobservable time-invariant differences among students (such as innate ability or motivation). We then estimate a cross-sectional OLS regression, which is similar to the Mincerian equations estimated in most of the previous literature, so that we can compare our estimates to the estimates that are available when it is impossible to observe the trajectory of wages.

First, we estimate our preferred individual fixed effects model, taking advantage of the existence of quarterly information on wages, where we compare the trajectory of wages among students who earn a specific type of credential and students who leave college without earning any credentials.

Model 1: The Individual Fixed Effect Model

$$\begin{aligned}\ln Wage_{it} = {} & \alpha + \beta(Credential_{it}) + \partial(Transfer_{it}) + \omega(Enrolled_{it}) \\ & + \lambda(Enrolled_{it} \times Credential_{it}) + \theta(Transfer_{it} \times Enrolled_{it}) \\ & + \psi(Time_{it}) + \xi(Intent \times Time_{it}) + \upsilon(Demographic \times Time_{it}) \\ & + \gamma(Time_{it}^{2}) + \omega(Intent \times Time_{it}^{2}) + \psi(Demographic \times Time_{it}^{2}) \\ & + \rho_i + \eta_t + \varepsilon_{it}\end{aligned}$$

$\ln Wage_{it}$ represents the natural logarithm of hourly wages for each individual in each quarter. Our wage records include four quarters before college entry and 29 quarters (about seven years) from initial entry, inclusive.

The key variable of interest is $Credential_{it}$, which represents a vector of dummy variables for each type of credential received at the Washington State community and technical colleges, including associate degrees, long-term certificates, and short-term certificates. Note that β represents the effect of credential for those not currently enrolled. This variable is coded 0 in all quarters before a student has earned a given credential (and is always coded 0 for students who never earn that credential). For each credential type, the corresponding variable (short-term certificate, long-term certificate, or associate degree) changes from 0 to 1 during the quarter in which the student first earns that credential, and is coded 1 for every quarter thereafter.

$Enrolled_{it}$ is a dummy variable that is set to 1 for every quarter during which the student is enrolled at any college (based on either Washington State community and technical college data or National Student Clearinghouse data) and 0 otherwise. This variable is included in order to account for the opportunity cost of being enrolled in school during a given quarter.

We also control for whether students transferred to a four-year institution by including a dummy variable, $Transfer_{it}$, which has the value of 1 for every quarter after a student has transferred to a four-year institution, and 0 otherwise.[24] Unlike Jepsen et al. (2011), we do not exclude from our sample students who eventually transfer to four-year institutions. Instead, we include an additional control for whether or not a student has transferred to a four-year institution during a given quarter.[25]

ρ_i represents individual fixed effects—that is, a dummy variable is included for each individual in the sample. The individual fixed effects control for all individual

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[24] We also test a model where we interact $transfer_{it}$ with the $Credential_{it}$ dummy for receipt of an associate degree to allow for the different effect of earning an associate degree and also transferring to a four-year institution, but the results change very little. Therefore, we do not include this interaction in the final model for ease of interpretation.

[25] Excluding students who eventually transfer—an exclusion conditional on an outcome—could result in biased estimates. That is, some of the students who never transfer may have desired to transfer but failed to do so because of their preexisting characteristics, and thus may have different potential outcomes compared with the rest of our comparison group. However, even though we control for whether or not a student has transferred, we do not highlight the coefficients for the effect of transferring because we believe we do not have a lengthy enough follow-up period nor information on receipt of a bachelor's degree in order to accurately estimate the effect of baccalaureate transfer.

characteristics (observed or unobserved) that do not change over time, such as innate ability or motivation.[26]

η_t represents absolute quarter fixed effects—that is, a dummy variable is included for each year and quarter in time (absolute, not relative to a student's entry). This is included in order to control for general labor market conditions during different quarters, and to account for the bias that could arise from some students entering the labor market during more favorable conditions than others due to differences in the length of credentials or students' length of college study.

The covariates in the second line of the equation include both a linear and a quadratic time trend ($Time_{it}$ and $Time^2_{it}$), which control for the non-linear effect of time on earnings. In addition, in order to control for any bias that may result from how student characteristics influence the trajectory of wages, we interact key student characteristics for which we have data (including demographic and intent variables) with the linear and quadratic time trends. The demographic variables include quintile of socioeconomic status, race (whether a student is White and non-Hispanic or not), and age at time of entry (19 or younger, 20–26, 27–45, or 46–60). The intent variables include two variables: a dummy variable indicating whether a student's track is for academic transfer or for workforce education, and a continuous variable that indicates

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[26] The individual fixed effects strategy is implemented by using the "areg" command in Stata.

the number of credits the student has enrolled in during the first quarter (enrollment intensity).

ε_{it} represents the error term.

The individual fixed effects model's objective is to estimate wage gains that result from credential receipt. Thus, in this model, we limit the sample to individuals who have some record of pre-college and post-college employment.

In this model, by including individual fixed effects, we control for all observable and unobservable time-invariant differences among students such as ability or motivation on wage levels. At the same time, by including demographic and intent controls interacted with the time trends, we control for how key observable student characteristics could affect the trajectory of wages over time. For example, as we show in Table 3-1, the intensity of course taking during the first quarter of enrollment is highly correlated with completion. If such differences among students also determine the trajectory of earnings, then we should control for their effect. This methodology improves over studies that estimate Mincerinan equations that can only control for observable differences among students, whereas we can control for both observable and unobservable differences among students that change the level of earnings. We are still not able to control for unobserved differences among students that affect the trajectory of earnings. The main identifying assumption of this model is that the wages before an individual earns a credential reflects that individual's human capital, and any changes in the trajectory of wages (compared with that of a student who has not earned a credential) can be attributed to earning a credential.

Second, in order to understand how our results would have been different if we had estimated a cross sectional model similar to the traditional Mincerian equation that is used in most of the previous literature, we estimate Model (2) below:

Model 2: Mincerian Equation

$$\begin{aligned}\ln Wage_{Q25-28} &= \alpha + \beta\left(Credential_{Q24}\right) + \partial\left(Transfer_{Q24}\right) + \omega\left(Enrolled_{Q25-28}\right) \\ &+ \lambda\left(Enrolled_{Q25-28} \times Credential_{Q24}\right) \\ &+ \theta\left(Transfer_{Q24} \times Enrolled_{Q25-28}\right) + \psi X + \varepsilon\end{aligned}$$

In the model above, $\ln Wage_{Q25-28}$ represents the natural log of wages during the seventh year after initial enrollment (quarters 25–28). The natural log of wages is used to account for the fact that the distribution of wages is skewed to the right.

$Credential_{Q24}$ represents a vector of dummy variables for each type of credential received at the Washington community and technical colleges, including associate degrees, long-term certificates, and short-term certificates. The value of each dummy variable for a specific type of credential is set to 1 if a student has earned that credential by the sixth year (24th quarter), prior to when the outcome of wages is measured.

$transfer_{Q24}$ indicates whether or not a student has transferred to a four-year institution by the 25th quarter. In order to account for the opportunity cost of attending college, we control for whether the student is still enrolled during any of the quarters 25 through 28, which are the quarters where earnings outcomes are measured and are used as the dependent variable. We do so by including the dummy variable $Enrolled_{Q25-28}$, which takes the value of 1 if the student was enrolled during any of those quarters. We also interact $Enrolled_{Q25-28}$ with $Credential_{Q24}$ and $Transfer_{Q24}$ in order to control for the possibility that opportunity costs may be different for students who continue to enroll in college after completing at least one credential or transferring to a four-year university.

We also control for a vector of observable student demographic characteristics *X*, which includes race, SES, gender, age (as well as age squared to allow age to have a nonlinear relationship with earnings), high school graduation or GED status, and family dependency status. In this Mincerian-type model, age is used as a proxy for work experience. We also control for the number of credits students enroll in during the first semester at the college (a measure of enrollment intensity), as well as the season of the student's initial enrollment and an indicator for whether the first college of attendance is located within the Seattle metropolitan area.

As explained earlier, this model is plagued with the selection bias problem: it is possible that the type of student who tends to earn higher wages is also the type of student who tends to earn a credential, which would lead to overestimating the returns to schooling or credential attainment. Our objective is to understand how closely a

Mincerian model would approximate the results that we would obtain by accounting for time-invariant observable and unobservable differences among students when the trajectory of wages or earnings is available.

As mentioned earlier, the sample of observations for these analyses that use hourly wages as their outcome is limited to those quarters that have wages available (i.e., those where a student is employed). Additionally, the sample of students is limited to those with some wage data both prior to initial enrollment and after college exit. However, estimates of returns to wages can be depressed if probability of employment for the sample increases, because more marginal workers (with potentially lower wages) would now be included in the portion of the sample participating in the labor market (Lee, 2009). Therefore, we should note that our estimates could reflect an underestimate of the true effect of credentials on wages.

3.4.2. Estimating the Effects of Earning a Credential on Probability of Employment and Hours Worked

In this section, we examine the effect of community college credentials on increasing employment. Examining employability as an outcome in addition to wages allows us to distinguish two distinct factors that would contribute to an increase in overall earnings: an increase in human capital as reflected by wage rates and an increase in hours worked or employment. Previous literature has mainly focused on examining the effect of community college schooling on earnings (for example, Kane & Rouse, 1995; Jacobson, LaLonde, & Sullivan, 2005; Jepsen et al., 2011). However, using earnings as an outcome incorporates several factors: wages, the probability of being employed, and the number of hours worked if employed. In this chapter, we separately examine the returns to these different components of earnings in order to isolate those labor market outcomes that are influenced by the receipt of community college credentials. This distinction allows us to understand roughly how much of the effect of credentials in increase in earnings is due to the increase in human capital reflected by higher wages, and how much is due to increase in employability or employment intensity.

In order to examine employability as an outcome, we estimate two models that examine the effect of credential attainment on both the likelihood of being employed and hours worked if employed. Here, we do not use the individual fixed effects model; while the trajectory of wages or earnings are meaningful, it is not helpful to examine likelihood of employment or hours worked in terms of trajectories because there are myriad reasons behind why students move in and out of employment over time. Instead, we introduce models that are similar to the Mincerian equation introduced in Model 2, but we also control for pre-college wages in addition to the other controls, in order to account for some of the unobserved preexisting differences among students that may be reflected in wages.

Model 3: The Effect of Credential Attainment on the Likelihood of Employment

$$
\begin{aligned}
&Employ_{Q25-28} \\
&\quad = \alpha + \beta(Credential_{Q24}) + \partial(Transfer_{Q24}) + \omega(Enrolled_{Q25-28}) \\
&\quad + \log Wage_{Q(-4)-(-1)} + \lambda(Enrolled_{Q25-28} \times Credential_{Q24}) \\
&\quad + \theta(Transfer_{Q24} \times Enrolled_{Q25-28}) + \psi X + \varepsilon
\end{aligned}
$$

In this model, the outcome is whether or not a student is employed during any quarter of the seventh year (quarters 25 to 28). The other variables in the model are identical to the Mincerian equation in 4.1, with the exception of $\log Wage_{(-4)-(-1)}$, which is the natural log of quarterly wages during the year prior to college enrollment (obtained from dividing the total earnings by the total hours worked during the four quarters prior to enrollment).[27]

Then, in order to understand the full picture of employability, we examine the effect of credential attainment on increasing the hours worked conditional on employment (Model 4). Model 4 is also a lagged wage model, and is identical to Model 3 except in that the outcome is hours worked 25 to 28 quarters after college entry.

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[27] If a student did not work during any of the quarters of the year prior to enrollment, then the student is excluded from our sample. Because the outcome of interest is whether or not a student is employed, students who do not have any wages during quarters 25 to 28 are included.

Model 4: The Effect of Credential Attainment on Hours Worked, Conditional on Employment

$$\begin{aligned} Hours_{Q25-28} &= \alpha + \beta\left(Credential_{Q24}\right) + \partial\left(Transfer_{Q24}\right) + \omega\left(Enrolled_{Q25-28}\right) \\ &+ \log Wage_{Q(-4)-(-1)} + \lambda\left(Enrolled_{Q25-28} \times Credential_{Q24}\right) \\ &+ \theta\left(Transfer_{Q24} \times Enrolled_{Q25-28}\right) + \psi X + \varepsilon \end{aligned}$$

Here, $Hours_{Q25-28}$ represents the average hours worked per week over the time period of quarters 25 through 28. Similar to the previous model, students are excluded from the model if they have not worked in any quarters during the year prior to college enrollment. In addition, because the outcome here is hours worked conditional on employment, we exclude all students who are not employed during the seventh year after college entry when the outcome is measured. Again, in Models 3 and 4, the outcomes of students who earn a specific credential type are compared with the outcomes of students who earn some credits but do not earn a credential.

3.4.3. Estimating the Wage Returns to Credentials Attainment in Different Fields

In order to study how the returns to credentials vary across fields, we estimate our same preferred individual fixed effects model (Model 1), but substitute each credential dummy variable with a vector of credential-within-field dummy variables $(Credential*Field)_{it}$. That is, earning an associate degree in allied health is coded in a separate variable from earning an associate degree in construction, so these associate degrees are allowed to have completely different effects on wage returns. All the other components of the model are exactly as those delineated in Model (1), which is our preferred fixed effects model. This model is described in Model F1:

Model F1:

$$\begin{aligned}\ln Wage_{it} = {} & \alpha + \beta(Credential_{it} \times Field_{it}) + \partial(Transfer_{it}) + \omega(Enrolled_{it}) \\ & + \lambda(Enrolled_{it} \times Credential_{it}) + \theta(Transfer_{it} \times Enrolled_{it}) \\ & + \psi(Time_{it}) + \xi(Intent \times Time_{it}) + \upsilon(Demographic \times Time_{it}) \\ & + \gamma(Time_{it}^2) + \omega(Intent \times Time_{it}^2) + \psi(Demographic \times Time_{it}^2) \\ & + \rho_i + \eta_t + \varepsilon_{it}\end{aligned}$$

In this model, we compare wage growth for students who earned a specific credential in a given field (for example, a long-term certificate in nursing) with students who enrolled in college but who did not earn a credential. Therefore, in this framework, we are assessing the value of a specific credential type in a given field, compared with the average value of the schooling that non-credentialed students earned, regardless of the field they were studying.

3.5. Results

3.5.1. Wage Returns to Credentials

Table 3-3 shows the results for our fixed effects models with sequentially added covariates, showing how we arrived at our preferred model. The first model (Model M1) is the most basic model using individual fixed effects. Model M2 adds in a control for whether or not the student is currently enrolled in either a two-year or four-year college in order to account for the opportunity cost of attending college. Model M3 adds an interaction between observable student characteristics and the time trend in order to control for any differential effects of observable preexisting student characteristics on wage growth. Model 4 adds interactions between intent and enrollment intensity and the time trend to control for the effect of the differences in students' intents (academic versus vocational) and the intensity of initial course enrollment.

The reason for including the time trend and interactions with student characteristics and intent/initial course enrollment is that it is possible that these observable factors not only affect the level of wages, but also affect the trajectory of wages over time; that is, they might affect the rate of growth in wages. Though there isn't much we can do to control for unobserved characteristics affecting the rate of wage growth, we can control for some key observed characteristics. We find that overall the coefficients are very stable and are not sensitive to different specifications. This could be because the individual fixed effects are doing the "hard work" of identification and there is little remaining bias that the addition of different controls can help reduce.[28]

The results from our final and preferred model (Model 4) indicates positive effects of long-term certificates on wages of 14.4 percent for women and 2.0 percent for men, and positive effects of associate degrees on wages of 8.3 percent for women and 3.6

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[28] Because it is possible that including a time trend may suppress the increase in wages that result from credential attainment, we also compare a model that excludes the time trend and its interactions entirely with a model that only adds the time trend and no interactions and find that the results are very similar.

percent for men. Short-term certificates do not seem to provide additional benefits to students: we see negative returns to earning short-term certificates for both women (−2.9 percent) and men (−0.2 percent), significantly so for women. These are wage advantages (or disadvantages in the case of short-term certificates) over students who earn some college credits but who do not earn a credential within seven years of initial enrollment. In order to better understand the value of the credentials, it is important to understand the comparison group. Most of the previous studies compare community college schooling with a high school diploma. However, in our dataset we only have information on students who enrolled in one of the Washington community and technical colleges; thus, we follow Jepsen et al. (2011) and compare students who earn a specific credential type with students who earn some credits but who do not earn any credentials.[29]

[29] The baseline comparison group, which consists of the students who do not earn a credential, earns on average 29 credits, which is substantial but lower on average than the credits earned by students who earn other credentials. Students who earn short-term certificates earn 44 credits on average; students who earn long-term certificates earn 100 credits on average; and students who earn an associate degree earn 116 credits on average.

Table 3-3: Preferred Fixed Effects Model with Sequentially Added Controls

	Females				Males			
	M1	**M2**	**M3**	**M4**	**M1**	**M2**	**M3**	**M4**
Short-term certificate	−0.0534***	−0.0573***	−0.0332***	−0.0289***	−0.0311***	−0.0363***	−0.00159	−0.00236
	(−0.0063)	(−0.00666)	(−0.00658)	(−0.0066)	(−0.00723)	(−0.00745)	(−0.00728)	(−0.00729)
Long-term certificate	0.129***	0.122***	0.141***	0.144***	−0.00943	−0.0161**	0.0225***	0.0200***
	(−0.00547)	(−0.00578)	(−0.00571)	(−0.00575)	(−0.00715)	(−0.00741)	(−0.00724)	−0.00728)
Associate degree	0.0850***	0.115***	0.0860***	0.0831***	0.0692***	0.0847***	0.0367***	0.0355***
	(−0.00297)	(−0.00334)	(−0.00332)	(−0.00334)	(−0.00326)	(−0.00361)	(−0.00355)	(−0.00357)
Currently enrolled		X	X	X		X	X	X
Includes demographic controls			X	X			X	X
Includes intent controls				X				X
n (observations)	281,077	281,077	281,077	281,077	316,816	316,816	316,816	316,816
n (students)	11,340	11,340	11,340	11,340	12,881	12,881	12,881	12,881
R-squared	0.594	0.596	0.608	0.608	0.707	0.708	0.723	0.723

Note. Robust standard errors in parentheses. Currently enrolled includes a dummy for whether the student is enrolled in a given quarter, as well as interaction terms between that dummy and each level of credential received. Demographic controls include SES, age category, and non-White interacted with the time trends. Intent controls include transfer or workforce intent, and the number of credits attempted in the first quarter, interacted with the time trends. Adapted from authors' calculations using student unit-record data for first-time students who attended any of the 34 community and technical colleges in Washington State during the 2001–2002 academic year.
*$p < .10$. **$p < .05$. ***$p < .01$,.

In order to compare our results with Jepsen et al. (2011), who use earnings as their primary outcome, we also estimated a model similar to Model 1 but that uses adjusted quarterly earnings (expressed in 2005 dollars) as the outcome (results not presented in table). Jepsen et al. found that associate degrees and long-term certificates (called diplomas in Kentucky) have quarterly earnings returns of nearly $2,000 for women, compared to returns of approximately $1,500 for men, while certificates have small positive returns for men and women. Our results show a relatively similar pattern to the estimates of Jepsen et al. in Kentucky, but our estimates are somewhat lower in general. Specifically, we find that a short-term certificate *decreases* female students' earnings by $142 ($p$ < .01) and male students' earnings by $26. A long-term certificate increases female students' earnings by $1,319 ($p$ < .01) and male students' earnings by $162 ($p$ < .05). Associate degrees increase female students' earnings by $784 ($p$ < .01) and male students' earnings by $381 ($p$ < .01). In both studies, the comparison group includes students who earn some credits (an average of 29 credits in our sample), but who do not earn a credential. The different estimates obtained between the two studies could be due to differences that exist between the labor markets in Washington and Kentucky, or differences in the breakdown of fields of credentials earned, or relatively minor methodological differences between our two studies.[30]

[30] Washington and Kentucky have labor markets that are substantially different. For example, Washington State has tended to have the highest minimum wage rate in the country, while Kentucky's minimum wage has generally not been higher than the federal rate.

Comparing the individual fixed effects estimates to regression estimates. Next we test how our results would be different if we were only able to estimate a cross-sectional Mincerian equation, similar to most of the previous literature (which would be estimated if one only had a cross-section of data). Using an Ordinary Least Squares (OLS) regression, we control for as many observable student characteristics as possible, using the same sample of students and a student's average wage in quarters 25 through 28 as the outcome. As Table 3-4 shows, the wage returns using OLS yield somewhat higher returns, with the exception of short-term certificates for men. This suggests that students who pursue long-term certificates and associate degrees are positively selected, compared with students who only earn some credits. It is also noteworthy that while there is a difference of a few percentage points in the OLS results, the OLS estimates are a reasonable approximation of the individual fixed effects results.

Table 3-4: Comparison of Estimates from OLS and Individual Fixed Effects Models

	Females		Males	
	OLS	**Individual fixed effects**	**OLS**	**Individual fixed effects**
Short-term certificate	−0.0175	−0.0289***	−0.0756*	−0.00236
	(−0.029)	(0.00660)	(0.0443)	(0.00729)
Long-term certificate	0.183***	0.144***	0.0688**	0.0200***
	(0.0302)	(0.00575)	(0.0295)	(0.00728)
Associate degree	0.102***	0.0831***	0.0878***	0.0355***
	(0.0137)	(0.00334)	(0.0137)	(0.00357)
n (observations)	11,340	281,077	12,881	316,816
n (students)	11,340	11,340	12,881	12,881
R-squared	0.065	0.608	0.123	0.723

Note. Robust standard errors in parentheses. Adapted from authors' calculations using student unit-record data for first-time students who attended any of the 34 community and technical colleges in Washington State during the 2001–2002 academic year.
**p* < .10. ***p* < .05. ****p* < .01.

Sensitivity checks. In choosing our preferred methodology, we face an inherent tradeoff between internal validity and external validity. In this section, we consider several possible threats to internal and external validity that could arise from our specific methodological choices. We show that estimates from our preferred methodology are robust to selecting alternate samples reflecting different methodological choices.

Table 3-3 shows the results for the sensitivity analysis for women and Table 3-4 shows the results for the sensitivity analysis for men. In both Table 3-3 and Table 3-4, the first column represents our main estimation results.

One concern may be that including teenagers in the sample may reduce the estimates' internal validity, because for students who are 19 or younger, pre-college wages might be from after-school or summer jobs that would not be appropriate predictors of wages later in life and are not an accurate indication of a pre-college human capital. However, if it is possible to include this sample of students, it would be preferable; they make up a significant portion of the community college population, and are often the population of greatest interest to policymakers. Model S2 excludes all individuals who are 20 or younger at time of initial enrollment in the college to test whether or not the estimates are sensitive to the inclusion of this group.

Another concern might be that students who are still enrolled in college toward the end of our data collection window of seven years might not have enough time in the labor market to have valid post-exit wages. Model S3 tests this by excluding individuals who are still enrolled during any of our last two years of data. Alternatively, we might not trust the quarters immediately prior to college enrollment, since these quarters may be associated with an "Ashenfelter dip."[31] Models S4 and S5 test this by excluding the

[31] The Ashenfelter dip is a decrease in earnings that may appear immediately prior to entering in a vocational training program, since individuals may be more likely to enter such a program shortly after losing employment, or may discontinue employment in preparation for entering the program.

quarter immediately prior to entry and the two quarters immediately prior to entry, respectively.

A final concern is that we err on the wrong side of maximizing internal validity (versus external validity) by limiting our sample to students who have both wages prior to enrollment and post-exit. In our preferred model, we had excluded all students from our sample if they had no wage records prior to entering college, or if they had no wage records after they exited college. The reason for making these exclusions was to obtain estimates that reflected the true "value added" to wages that results from obtaining college credentials. The tradeoff is that the results may not be generalizable to students who do not have either pre- or post-college wages. To test whether the results are robust to including students who do not have pre- or post-college wages, we add in students without pre-enrollment wages (in S6), without post-exit wages (in S7), and everyone whether or not they have pre- or post- college wages (in S8). In these cases, we code quarters during which a student does not have wages (whether they are before, during, or after college attendance) as having missing wages.

As the estimates in Table 3-5 and Table 3-6 indicate, the results are generally robust to alternate samples. In other words, the general story about the returns to different credential types is not sensitive to the sample adjustments discussed above. The fact that our sample is not sensitive to whether or not we include students who do not have prior wages could be because only 26 percent of students in the sample are missing the information. Furthermore, because we may still have wages for these students while they are enrolled in colleges, there is at least partial information about pre-credential wages for these students.

The only estimate that seems to be especially sensitive to an alternate sample specification (a difference of 3 percentage points or more) is the estimate of long-term certificates for men when we exclude teenagers (Model S2). When we exclude individuals who are 20 years old or younger from the sample, the return to wages is increased by about 4 percentage points. Thus it seems that for older males (who may be more likely to be displaced workers), long-term certificates lead to a 6 percent increase in wages, which is not insubstantial.

Table 3-5: Sensitivity Check of Fixed Effects Model, Females Only

Females	**S1**	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**
Short-term certificate	−0.0289***	−0.0449***	−0.0225***	−0.0314***	−0.0330***	−0.0188***	−0.0347***	−0.0224***
	(0.00660)	(0.0102)	(0.00789)	(0.00689)	(0.00729)	(0.00631)	(0.00679)	(0.00621)
Long-term certificate	0.144***	0.172***	0.145***	0.148***	0.152***	0.164***	0.149***	0.165***
	(0.00575)	(0.00864)	(0.00662)	(0.00592)	(0.00616)	(0.00541)	(0.00588)	(0.00536)
Associate degree	0.0831***	0.0872***	0.0751***	0.0838***	0.0826***	0.0827***	0.0829***	0.0822***
	(0.00334)	(0.00413)	(0.00376)	(0.00342)	(0.00351)	(0.00306)	(0.00340)	(0.00304)
n (observations)	281,077	153,305	230,954	271,614	261,726	339,711	285,889	359,131
R-squared	0.608	0.487	0.613	0.610	0.612	0.609	0.611	0.61

Note. Robust standard errors in parentheses. S1 = base model; S2 = excludes 20 or younger; S3 = exclude those individuals who are enrolled after five years (the last two years for which we have data); S4 = exclude (set to missing) all observations one quarter before enrollment (Ashenfelter dip); S5 = exclude one and two quarters prior to enrollment in college (Ashenfelter dip); S6 = include individuals who do not have wages prior to college entry and set the wage to missing in those quarters; S7 = include individuals who do not have post-colleges wages- set the wages to missing in those quarters; S8 = including those without wages in pre and post college period- set missing periods to missing in those quarters. Adapted from authors' calculations using student unit-record data for first-time students who attended any of the 34 community and technical colleges in Washington State during the 2001–2002 academic year.
*p < .10. **p < .05. ***p < .01.

Table 3-6: Sensitivity Check of Fixed Effects Model, Males Only

Males	S1	S2	S3	S4	S5	S6	S7	S8
Short-term certificate	−0.00236	0.0203*	0.00823	−0.00398	−0.00667	0.000985	−0.000628	0.00556
	(0.00729)	(0.0121)	(0.00784)	(0.00763)	(0.00815)	(0.00718)	(0.00751)	(0.00705)
Long-term certificate	0.0200***	0.0601***	−0.00560	0.0272***	0.0372***	0.0349***	0.0276***	0.0346***
	(0.00728)	(0.0128)	(0.00802)	(0.00754)	(0.00791)	(0.00703)	(0.00750)	(0.00698)
Associate degree	0.0355***	0.0526***	0.0405***	0.0393***	0.0425***	0.0372***	0.0410***	0.0397***
	(0.00357)	(0.00454)	(0.00386)	(0.00365)	(0.00376)	(0.00331)	(0.00363)	(0.00328)
n (observations)	316,816	157,076	274,892	306,305	295,171	372,386	322,016	393,423
R-squared	0.723	0.682	0.727	0.724	0.726	0.718	0.724	0.719

Note. Robust standard errors in parentheses. S1 = base model; S2 = excludes 20 or younger; S3 = exclude those individuals who are enrolled after five years (the last two years for which we have data); S4 = exclude (set to missing) all observations one quarter before enrollment (Ashenfelter dip); S5 = exclude one and two quarters prior to enrollment in college (Ashenfelter dip); S6 = include individuals who do not have wages prior to college entry and set the wage to missing in those quarters; S7 = include individuals who do not have post-colleges wages- set the wages to missing in those quarters; S8 = including those without wages in pre and post college period- set missing periods to missing in those quarters. Adapted from authors’ calculations using student unit-record data for first-time students who attended any of the 34 community and technical colleges in Washington State during the 2001–2002 academic year.
***$p < 0.01$. **$p < 0.05$. *$p < 0.1$.

3.5.2. Probability and Intensity of Employment as Outcomes

Other prior research has looked at the increase in students' earnings after graduation (Jepsen et al., 2011). As discussed earlier, using earnings as an outcome incorporates several factors, including wages, the probability of being employed, and the number of hours worked if employed. Therefore, wage increases account for only part of an increase in earnings. To better understand the full impact of credential receipt upon labor market entry, we also examine students' probability of employment and hours worked weekly as outcomes.

As we explained earlier, the individual fixed effects methodology may not be as appropriate for examining probability of employment and hours worked, because the likelihood of being employed or of working part time *prior* to college entry may not be a strong predictor of the likelihood of being employed or working part time *after* college, given confounding factors such as prior enrollment in full-time education (including high school) and parenthood. Thus we use the lagged wage model to estimate the effects of credential attainment on the likelihood of employment and hours worked conditional on employment.

As Table 3-7 indicates, long-term certificates and degrees have a strong, positive impact on students' likelihood of employment, and a more modest positive impact on hours worked per week for those who are employed. Earning an associate degree increases the probability of a student's being employed during the seventh year after initial enrollment by 11 percentage points for women and 8 percentage points for men.

Similarly, long-term certificates increase the probability of employment 9 percentage points for women and 11 percentage points for men. However, short-term certificates don't seem to have a strong impact on being employed: the impact on both the probability of employment and hours worked weekly is indistinguishable from 0 for both men and women.

These employment effects have important implications for our interpretations of the wage effects. Given that associate degrees and long-term certificates increase the likelihood of employment, they affect the composition of the labor force by inducing some marginal workers who would not have found a job in the absence of the credential to find work. As a result of this change in the composition of the labor force, it is likely that the marginal workers that are now working are those with the lowest levels of human capital and the lowest wages. This change in the composition of workers is likely to lead to an underestimate of the returns to associate degrees and long-term certificates. By contrast, because we do not find an employment effect for short-term certificates, we do not expect a similar negative bias in our estimates of the returns to short-term certificates.

Table 3-7: Effects of Credential Attainment on Probability of Employment and Hours Worked

	Females		**Males**	
	Hours Worked Weekly[a]	**Probability of Employment**	**Hours Worked Weekly[a]**	**Probability of Employment**
Short-term certificate	0.373	0.0224	0.223	−0.0735
	(0.697)	(0.0296)	(0.976)	(0.0977)
Long-term certificate	1.800**	0.0857***	0.681	0.111***

	(0.683)	(0.0195)	(0.831)	(0.0180)
Associate degree	0.882**	0.112***	2.256***	0.0761***
	(0.340)	(0.0133)	(0.358)	(0.0149)
n (observations)	9,235	12,688	10,462	14,483
n (students)	9,235	12,688	10,462	14,483
R-squared	0.044	0.030	0.053	0.024

Note. Robust standard errors in parentheses. Adapted from authors calculations using student unit-record data for first-time students who attended any of the 34 community and technical colleges in Washington State during the 2001–2002 academic year
[a] The model with hours worked weekly as an outcome is run conditional on some employment during the seventh year after enrollment.
*p < .10. **p < .05 ***p < .01.

3.5.3. Returns to Credentials, by Field of Study

Decisions about which level of credential a student should pursue are certainly not made in a vacuum. The length of a program (and subsequent opportunity cost) and the type of credential ultimately attained are important factors in this decision. However, it's also possible that students may choose a field of study first, and then make a decision about which level of credential to pursue. In this case, the question isn't so much, "Should I get a long-term certificate or an associate degree?" but rather, "Should I train to become a medical receptionist or a medical assistant?" At Renton Technical College, for example, there is a 47-credit Medical Receptionist certificate and a 105-credit Medical Assistant associate degree. If this is the case, the effect of receiving each level of credential may depend strongly on the field of that credential.

To test this, we examine returns to credentials separately by field. Our taxonomy of field of study was adapted from the NCES classification of CIP codes using our knowledge of programs offered in Washington State. Categorizing fields of study is a process that involves tradeoffs: on the one hand, it would be ideal for substantively different programs leading to distinct occupations to be categorized separately. On the other hand, to have sufficient power to run the analysis across fields, a threshold must be met for the number of students in that field. For that reason, some distinct but relatively small programs (such as cosmetology, culinary services, and administrative services) had to be grouped together. These three programs, at least, had demographically similar profiles. Similarly, mechanics and repair (including, for example, automotive programs) and precision production (including welding) were merged into one category, which seemed appropriate, given that both represent male-dominated vocational fields with a large amount of lab time and hands-on activity.

Another reason it is important to examine credentials by field of study is that there is tremendous variation in the breakdown of credentials offered across these fields of study. Table 3-8 shows the number of students in our sample who earned a given type of credential in each field. Regardless of gender, associate degrees are dominated by awards in humanities and social sciences—that is, traditional liberal arts degrees, most of which are designed to transfer to baccalaureate institutions. For women, long-term certificates are dominated by awards in allied health and nursing, and to a lesser extent, cosmetology, culinary, and administrative services. Those fields, as well as business and marketing, are also prominent in short-term certificates for women. However, for men, certificates are less skewed toward a couple of single fields, though mechanics, repair, and welding has the highest number of graduates of both short-term and long-term certificates.

Table 3-8: Number of Students in Each Credential Level and Field of Study Combination

	Females			Males		
	Associate degree	**Long-term certificate**	**Short-term certificate**	**Associate degree**	**Long-term certificate**	**Short-term certificate**
Humanities and social sciences	1,707	0	7	1,214	3	1
Math and science	9	0	0	34	0	0
Information science, communication, and design	67	21	16	158	65	55
Engineering sciences	22	8	12	134	29	37
Allied health	150	226	134	38	47	51
Nursing	129	176	128	18	35	16
Mechanics, repair, and welding	8	4	8	157	96	87
Protective services	11	2	10	53	11	16
Construction	3	0	14	29	9	26
Business and marketing	143	39	70	82	21	25
Education and childcare	41	22	27	1	0	1
Transportation	1	0	4	3	33	80
Cosmetology, culinary, and admin services	88	88	74	13	17	11
Other CTE/not assigned	2	1	0	1	0	9

Note. Adapted from authors calculations using student unit-record data for first-time students who attended any of the 34 community and technical colleges in Washington State during the 2001–2002 academic year. Sample sizes smaller than 10 were omitted from the analysis of returns to credentials by field of study and combined into the “other” category.

A priori, it is possible that field of study determines a student's occupation upon graduation, which could have the largest effect on wage; the level of credential could be unimportant compared to the field of that credential. To test which fields of study are "high-return," we run our individual fixed effects model but allow each combination of credential level and field of study to have its own separate dummy variable to capture the returns to earning that credential in that field only. Dummy variables for each credential level and field combination are all included in a single model. Results are reported in Table 3-9, however, with three separate columns for each credential level, for the sake of readability.

Short-term certificates do not, overall, show a great deal of value in terms of wage increases for students who earn them. However, there is a fair amount of variation among the coefficients. A number of short-term certificates even seem to have significant negative returns (compared to attending college but not earning a credential). Even students pursuing nursing, traditionally thought of as a high-return field, see negative returns to earning a short-term certificate (which would lead to becoming a nursing assistant or nursing aide, rather than a licensed practical nurse or registered nurse). On the other hand, there are some fields where short-term certificates do seem to have value: short-term certificates in protective services for men lead to particularly high (and significant) wage increases of 22.2 percent, while in transportation, those returns are 6.1 percent.

For long-term certificates, the variation is even more significant. Despite women seeing impressively large returns to long-term certificates overall, only allied health and nursing are associated with significant, positive returns. For women, earning a long term certificate in allied health increases wages by 6 percentage points and earning a long term certificate increases wages by 29 percentage points. However, it isn't only the larger number of women in these fields that accounts for higher overall estimates of returns to long-term certificates for women compared to men. In fact, returns to long-term certificates are lower for men than for women in nearly every field of credential in which adequate numbers of individuals earning that credential makes comparison warranted. Some long-term certificates for men do result in positive, significant returns; in particular, returns to nursing long-term certificates are 20.4 percent for men, and returns to transportation long-term certificates are 13.2 percent.

Associate degrees lead to positive returns across almost every field of study. There is variation in the magnitude of these awards (for example, nursing degrees lead to the highest returns for both women and men, 37.0 percent and 26.8 percent respectively, but associate degrees in humanities increase earnings by only about 5 percent). However, unlike the other credentials, there are almost no associate degree and field combinations that have zero or non-significant returns (none for women, and only a couple for men). Despite the fact that our overall estimates indicated it was more valuable for women to earn a long-term certificate than an associate degree, our field-specific results suggest that a more nuanced view is necessary. The high overall returns to long-term certificates are driven by the large number of certificates in allied health and especially nursing; the lower returns to associate degrees are driven mostly by degrees in humanities and social sciences.[32] In any given field (for example, nursing), it is still preferable to earn the associate degree.

Other studies (Grubb, 1997; Jepsen et al., 2011) have found large returns to credentials in healthcare, which encompasses both nursing and allied health. It is useful to note that both long-term certificates and associate degrees in nursing lead to much higher returns than the other corresponding credentials in allied health, suggesting there is a need to break down the healthcare field in more detail.

[32] It is worth noting that most associate degrees in the humanities and social sciences are designed to transfer to baccalaureate institutions and may leave the door open to further education, which could result in higher returns if we followed students for a longer period. Many occupational associate degrees, on the other hand, are terminal. See Hanushek, Woessmann, and Zhang (2011) for some discussion of the relative labor-market advantages of vocational and general education programs over time.

Table 3-9: Estimates of Wage Returns to Credentials by Field of Study

	Females			Males		
	Short-term certificates	Long-term certificates	Associate degrees	Short-term certificates	Long-term certificates	Associate degrees
Humanities and social sciences			0.0492*** (0.00391)			0.0139*** −0.00451
Science and mathematics						0.207*** −0.0212
Information science, communication, and design	−0.0472 (0.0384)	0.0372 (0.0302)	0.0366** (0.0158)	−0.0568*** (0.0183)	−0.0237 (0.0178)	−0.00941 −0.0112
Engineering sciences	−0.0608 (0.0398)		0.0788*** (0.0264)	−0.0240 (0.0250)	−0.0429 (0.0266)	0.0793*** −0.0113
Allied health	−0.0328*** (0.0118)	0.0600*** (0.00873)	0.138*** (0.0105)	0.0135 (0.0192)	−0.0148 (0.0186)	0.135*** (0.0195)
Nursing	−0.0581*** (0.0126)	0.290*** (0.0104)	0.370*** (0.0118)	−0.0960*** (0.0369)	0.204*** (0.0223)	0.268*** (0.0295)
Mechanics, repair, and welding				−0.0588*** (0.0153)	0.0148 (0.0138)	0.0716*** (0.0100)
Protective services	0.00169 (0.0395)		0.141*** (0.0344)	0.222*** (0.0282)	0.0267 (0.0364)	0.0825*** (0.0164)
Construction	0.121** (0.0487)			−0.0208 (0.0306)		0.140*** (0.0235)
Business and marketing	−0.0732*** (0.0164)	0.0225 (0.0233)	0.0398*** (0.0107)	0.0401 (0.0282)	−0.139*** (0.0312)	0.00769 (0.0139)
Education and childcare	0.0420* (0.0239)	−0.0786*** (0.0301)	0.0607*** (0.0190)			
Transportation				0.0606*** (0.0180)	0.132*** (0.0247)	
Cosmetology, culinary, and administrative services	0.00670 (0.0165)	−0.0558*** (0.0142)	0.0517*** (0.0131)	−0.176*** (0.0484)	−0.179*** (0.0309)	−0.0523* (0.0309)
Other	0.0462 (0.0320)	0.0274 (0.0364)	0.132*** (0.0261)	−0.0148 (0.0458)	0.161*** (0.0371)	−0.144*** (0.0557)
Overall estimate to credential from separate model without fields	−0.0289*** (0.00660)	0.144*** (0.00575)	0.0831*** (0.00334)	−0.00236 (0.00729)	0.0200*** (0.00728)	0.0355*** (0.00357)

Note. Robust standard errors in parentheses. Adapted from authors' calculations using student unit-record data for first-time students who attended any of the 34 community and technical colleges in Washington State during the 2001–2002 academic year.
$^*p < .10$. $^{**}p < .05$. $^{***}p < .01$

3.6. Discussion

This chapter adds more information to the emerging literature on the returns to community college credentials by providing evidence from the 2001–2002 cohorts of students from Washington State using a rigorous methodology. Our results suggest that some credentials lead to high returns to wages, but some do not; in addition, there are large variations by the field of credential. Overall, we find that there are substantial wage returns to long-term certificates and associate degrees for women (14 percent higher quarterly wages for obtaining a long-term certificate and 8 percent higher quarterly wages for obtaining an associate degree compared with attending a college and not obtaining a credential), and modest returns for men (2 percent increase in quarterly wages for long-term certificates and 3.6 percent increase in quarterly wages for obtaining an associate degree).[33] By contrast, we find that short-term certificates have no overall labor market value in terms of increasing wages.

Furthermore, our findings suggest that high returns to earnings that are found in some of the previous studies are likely to be partly driven by greater likelihood of employment and more hours worked, in addition to the increase in wages. For both men and women, associate degrees and long-term certificates have an important role in increasing the likelihood of employment and, to a lesser extent, hours worked. Earning a long-term certificate increases the likelihood of being employed by 9 percentage points

[33] However, as noted, there is some sample sensitivity to the estimate on long-term certificates for men; older workers may experience slightly higher wage returns of about 6 percent.

for women and by 11 percentage points for men, and increases hours worked for those who are employed by 1.8 more hours per week for women and about 0.7 hours per week (not significant) for men. Earning an associate degree leads to about 11 percentage points greater likelihood of employment for women and 8 percentage points for men. Short-term certificates do not seem to have any effect on employability for their graduates.

We find that there is greater variation to returns across fields of study within a given credential level than there is variation to returns across credential types. For example, earning an associate degree in nursing increases women's wages by 37 percent, whereas earning an associate degree in humanities and social sciences or information science, communication, and design increases wages by only 5 percent and 3.6 percent, respectively. Another important point is that simply comparing the average returns to associate degrees versus long-term certificates without regard to the field in which those credentials were earned is misleading. This is because, despite the substantially higher returns to long-term certificates for women, associate degrees yield higher returns to wages *within any given field*. The reason for the higher overall average returns to long-term certificates (compared to associate degrees) for women, is that the long-term certificates are more likely to be earned in high-return fields, particularly nursing. Furthermore, unlike Grubb (who found zero to negative returns to associate degrees in some fields), we find positive and significant returns to almost all associate degrees, even though in some fields the returns are much higher than in other fields.

Our analysis by field of study shows that most short-term certificates do not lead to improved labor market outcomes for students who complete them. Even allied health and nursing, which we found to be high-return fields for longer credentials, do not have positive returns for students who earn only a short-term certificate. That said, there were some exceptions, notably protective services and transportation for men. As we noted earlier, students who earn short-term certificates earn 44 credits on average, which is only 10 credits more than the average number of credits earned by the comparison group that enrolls but does not earn any credentials. Some possible explanations are that short-term certificates are earned in fields that are on average less valuable than the coursework that students accumulate when they are not pursuing a program. We can rule out the possibility that the only students who earn short-term certificates are those who cannot find jobs because we found that earning a short-term certificate does not effect the likelihood of employment. However, because we are unable to completely address selection bias, it is possible that selection bias is contributing to underestimating any value short-term certificates may have over and above the effect of earning 29 credits and not earning a credential.

Given our estimates of the lack of value of short-term certificates, supplementing the results of other recent studies, colleges should examine each short-term certificate program carefully and critically to ensure that it is serving students well. At the same time, it is important to note that even if a program is not increasing wages and employment for its graduates, it may still be beneficial in other ways—for example, by providing entry into an occupation that a student finds desirable for other, non-economic reasons.

This study contributes to the literature on the returns to community college in several ways. First of all, the only other study on this topic that attempts to control for unobserved student characteristics is by Jepsen et al. (2011), who used data from the state of Kentucky. Our analysis using data from Washington State complements the study by Jepsen et al. by providing evidence from a different state. As we discussed earlier, Washington data has several distinct advantages—for example, it is more nationally representative compared with Kentucky in terms of the distribution of community college credentials that are offered. Furthermore, our dataset has wage records available, which allows us to understand the value of credentials in terms of increasing human capital, not just earnings. Our dataset also allows for seven years of follow-up after initial enrollment at community college, which is a year and a half longer than Jepsen et al.'s cohort. Having a longer follow-up of students' labor market outcomes is particularly important for community college students, because many of them take several years before they graduate or exit the college and begin working full-time. In addition to providing evidence from a different state, a longer follow-up period, and estimates of returns to wages rather than earnings, another contribution of this chapter is that we have a somewhat more fine-tuned categorization of the field of study. This allows us to distinguish between, for example, allied health and nursing; other studies that do not distinguish between these two fields may find their returns to health care driven largely by extremely high returns to nursing credentials.

However, like most empirical literature, our study is not without limitations. First of all, the external validity of our results is limited, since these results are from Washington during 2001 to 2009. The returns to community college credentials may be different in other locations, and particularly after the so-called Great Recession that emerged in 2008. For this reason, we believe that it is important that similar research be conducted using data from different states and from other time periods. Secondly, even though we are able to account for most of the selection bias found in the previous literature, we are still unable to control for unobserved differences among students that affect the trajectory of wages. This may particularly be a problem in studying the returns to wages for traditional students, whose wages prior to entering college may not be a true reflection of their potential to earn. It is at least comforting that when we exclude teenagers from our sample, the returns to credentials do not change for most credential types (with the exception of long-term certificates for men). In general, we find that our results are very robust to various sensitivity checks.

Our study has important policy implications for state policymakers and community colleges. As we discussed earlier, possibly as a side effect of the shift of focus from enrollment to completion, there has been a dramatic increase in the number of short-term certificates offered by community colleges nationally. Although our study and the study by Jepsen et al. (2011) are the only rigorous studies that have examined the returns to short-term certificates, both studies find that these credentials have zero to very small returns. Thus, based on this emerging evidence, we believe that this dramatic national increase in the number of short-term certificates in the last decade may not have produced a commensurate increase in wages for those earning them. State policymakers may want to place greater value in investing in associate degrees and long-term certificates in high-return fields of study that are known to have positive impacts for students. More generally, we recommend that states and community colleges use this emerging evidence on the returns to different types of credentials in different fields when making decisions about program offerings. In particular, data collected for the use of reporting gainful employment statistics (as now mandated by the federal government for some programs) may provide a helpful barometer to program success. However, care should be taken in interpretation, since those statistics do not account for student selection into particular programs in the first place. Finally, we believe that every state should conduct similar analysis on the labor market returns of the credentials that they offer. States should not only use the information to make decisions about program offerings, but also make the information about labor market returns to different programs and credentials available to students alongside information on graduation rates. That way, students who attend college primarily to find a career in which to earn a living wage can make informed decisions about which program would be best to pursue.

Afterword

Community colleges face many challenges in accomplishing their mission to provide skilled labor necessary for the United States' economic growth and reduce the post-secondary attainment gap between students from minority and low-SES backgrounds and their more advantaged counter parts. As Bailey and Morest document in their book *Defending the Community College Equity Agenda,* Community Colleges receive less financial resources per student compared with four-year public universities, and yet they serve students who are in much greater need for academic support (Bailey & Morest, 2006).

Community college students face several challenges in their path to completing a credential. As open access institutions, many community college students are identified to be unprepared for college level work and may have to catch up; yet, given the limited financial resources many of these students face, they tend to have less time available to study as many spend long hours in paid employment. The essays in this dissertation attempts to shed light on how these challenges affect community college students' success with the goal of informing policymakers about effective strategies to help them. While this dissertation, like any other individual piece of research, can not fully explain the causes and conditions that would improve community college student outcomes, it has several implications for policy and highlights areas where future research should focus on.

The essays in this dissertation have important policy implications. The results from the first chapter on the effectiveness of the lowest level of mathematics education, adds evidence to the growing body of literature that finds students identified to have different degrees of remedial need do not benefit and in cases are even harmed by being required to take multiple remedial classes with no college credit. Several states and colleges have already began to experiment with alternatives to multiple levels of remedial education that reduce the length of remedial sequence or eliminate remediation and provide additional support for students with greater need (for a summary of different redesign initiatives see Rutschow & Schneider 2011; Edgecombe 2011). Redesigning the traditional model of remedial education with the goal of reducing the time and money spent on non-credit remedial coursework, is a strategy that can be implemented without additional resources and may even bring about cost savings. The evidence from this dissertation and similar research show that alternatives such as accelerating the traditional model of remedial sequence is likely to bring about improvements in student outcomes. Although existing evidence on the effectiveness of remediation is based on results that are "local" and do not strictly show that all levels of remediation could be eliminated without any harm to students, the results are highly suggestive. Future research on remediation should focus on evaluating the value of acceleration strategies and other similar developmental education redesign in comparison with having multiple levels of remediation. By taking such direction, future research can help us understand both the improvements that can be expected from alternatives models of remediation as well as help identify the most effective alternatives.

Student employment, unlike remediation, is an area that colleges do not have direct control over. Instead, students are the ones making the decision about how much to work while enrolled in college. Yet, if student employment is the primary cause for the low-completion rates of the community college students then, there may be little community colleges can do to improve student persistence. Therefore, it is crucial to understand how much the poor academic outcomes of students at community colleges are the result of their employment situation. This dissertation shows that unlike what Stinebrickner and Stinebrickner (2003) found at Berea college, small increases in employment does not have large negative consequences for community college students' academic achievement, at least when first year GPA and credit accumulation are considered.

Finally, a potential solution to the low-completion rates of community college students is offering short-term career focused credentials that may not require rigorous coursework and even underprepared students could complete without the need for remediation. At the same time, such short-term credentials which can be completed in less than a year, would reduce the financial burden on students and reduce the need for working long hours while also studying. These reasons may explain the enthusiasm for and the growth in the number of short-term certificates during the last decade. The evidence provided in this dissertation suggests that short-term certificates do not bring about the same large increases in earnings that result from attaining a long term certificate or an associate degree. Therefore, despite the fact that short-term certificates may have higher completion rates, compared with other credentials, they seem to have substantially lower labor market outcomes, which undermines their appeal as a solution to combating the challenges of low academic preparation and limited financial resources that community college students face. At the same time, given that associate degrees tend to have substantial returns in every field of study, their completion can help community college students boost their wages.

Taken together, the chapters of this dissertation suggest that there are things community colleges can do to help improve students' persistence, even though those solutions may not be always easy to implement. This dissertation shows that while the national shift from credentials that require a year or more of coursework to complete towards credentials that require less time to complete, seems to have adverse labor market consequences for students, the length of study may be reduced in other ways that could help students. In particular, reducing the number of remedial courses is one way to reduce the length of study and can be done without any costs in terms of academic outcomes or labor market outcomes while improving completion rates.

Finally, this dissertation highlights specific areas that future research should focus on. While evidence from this dissertation suggests that students would benefit from fewer remedial courses, limited rigorous research is available that provides evidence of the effectiveness of alternative models based on the ideas of acceleration and mainstreaming and condensed courses (Edgecome 2011). Another question that this dissertation leaves unanswered is the effect of starting to work long hours, perhaps going from working ten hours or less to working full time. Although administrative data suggests that the number of community college students who work full-time may be fewer than students' self-reports of work intensity suggests, there a substantial number of community college students that work long hours. Causal studies that are able to examine the effect of working at different levels of intensities can help us understand the full picture of the consequences of student employment. Finally, while this dissertation suggests that short-term certificates are less effective in increasing wages and employability compared with Associate Degrees and long term certificates, it is not exactly clear why that is so. Qualitative studies can help shed light on the differences between program requirements, employee expectations, and some of the reasons behind the differences between the labor market value of different credentials.

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